

## **ABSTRACT**

CANTWELL, APRIL RENÉE. Improving the Prediction of Commitment and Innovative Work Behavior from Climate for Innovation Perceptions: An Application of Latent Profile Analysis. (Under the direction of Samuel B. Pond, III.)

In this research study, I conceptualized climate for innovation perceptions as representing subjective interpretations of the environment, and also as representing a complex and dynamic interaction between people and environments. Simple variable approaches and, as demonstrated by Young and Parker (1999), simple aggregation of climate survey scores to formal organizational groups seems inadequate to represent this complexity. The use of clustering techniques to identify homogeneous groups with regard to perceptions of climate (e.g., Schneider & Reichers, 1983; Mathisen & Einarsen, 2004; Joyce & Slocum, 1984) is an approach that can represent data complex interactions of people and environments. Researchers have not yet determined which clustering techniques best account for the complex influences on perceptions of climate or best predict associated organizational outcomes.

Latent profile analysis (LPA) is a clustering technique that may move the climate research forward. I used LPA to classify individuals by their climate for innovation perceptions and simultaneously to assess the relative contributions of situational and individual difference covariates, including company membership, functional membership, organizational level, and organizational tenure. Latent class membership was used to predict affective, normative, and continuance (ANC) commitment to the organization; ANC commitment to innovation, creative innovative work behavior (IWB), and implementation IWB to determine if latent class membership predicted these outcomes beyond the contribution climate for innovation perceptions.

The archival dataset included 1,891 individual respondents from four high-technology firms. Only 383 cases provided commitment and IWB outcome data for the predictive study. The Innovation-Capacity Climate Survey (ICCS) measured nine dimensions of the climate for innovation, including Meaningful Work, Risk Taking, Customer Orientation, Agile Decision Making, Business Intelligence, Open Communication, Empowerment, Business Planning, and Learning Organization (Aiman-Smith, Goodrich, Roberts, & Scinta, 2005). A six-factor adaptation of Meyer and Herscovitch's (2001) ANC commitment model measured ANC commitment to the organization and ANC commitment to innovation. A two-factor adaptation of Dorenbosch, van Engen, and Verhagen's (2005) IWB scales measured Creative and Implementation IWB. The nine ICCS

scales, four of six commitment scales, and both IWB scales demonstrated acceptable confirmatory factor analysis fit, maximal and internal consistency reliability, and expected factor interrelationships.

After I identified three viable latent class solutions using LPA, I used multivariate analysis of variance (MANOVA) to examine the relationships among situational and individual difference covariates. I concluded that individual differences contributed more to perceptions of climate for innovation than did situational variables. I next used multivariate analysis of covariance (MANCOVA) to test whether latent class membership predicted commitment and IWB, with ICCS scores entered as covariates. For two latent class solutions, class membership predicted normative commitment to innovation; for one solution, class membership predicted IWB. Power and effect sizes for all of these analyses were low. Finally, I tested the hypotheses that climate perceptions decrease with increasing organizational tenure at the group and company level. Neither test was statistically significant but, at the company level, effect sizes were moderate and sample size was small.

In sum, I sought to explore climate perceptions as a complex interaction of situation and individual differences. Although not conclusively so, I demonstrated that latent class membership was related to individual differences and situational factors, and that it predicted commitment and IWB. Future research should include person and situation variables, and models should be designed to assess the complex interactions among these variables. LPA modeling is a promising technique for understanding climate in organizations and important organizational outcomes consistent with my viewpoint.

Improving the Prediction of Commitment and Innovative Work Behavior from Climate for Innovation  
Perceptions: An Application of Latent Profile Analysis

by  
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**Dedication**

For Lakin Obare and John Obare, who inspire me and make me proud every day.

### **Biography**

April Renée Cantwell was born to Ellis Neal Cantwell and Elaine Hazel Blanchard Cantwell in Gettysburg, PA on July 7, 1970. She was raised in Taneytown, MD and graduated from Francis Scott Key High School in Union Bridge, MD in 1988. In 1999, she earned a Bachelor of Science degree in Psychology from Morgan State University in Baltimore, MD. She earned a Master of Science degree in Psychology from North Carolina State University in Raleigh, NC in 2001. She currently works as a research consultant, conducting occupational research for the National Center of O\*NET Development on behalf of North Carolina State University.

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## **Introduction**

There is sufficient evidence in the psychological literature to suggest that individual perceptions of a climate for innovation strongly and positively relate to outcomes such as innovative work behavior, commitment to the organization, and commitment to innovation. These relationships, which occur at the individual level, show that when an individual perceives that the work environment is innovative, he or she demonstrates stronger affective commitment to the organization and innovation, and is likely to perform innovative work behaviors. Although organizational researchers and practitioners often want to make inferences at a higher level of aggregation than the individual-level, there is insufficient evidence to conclude that all individuals in the same environment perceive that environment in the same way. Nor is there sufficient evidence to conclude that individuals in the same environment feel equally committed or perform innovative behaviors to the same extent. Therefore, addressing climate for innovation research at an individual level seems most appropriate and effective.

This study represents a step toward greater understanding of psychological climate, particularly the psychological climate for innovation. It aims to identify whether individual differences affect the relationships between perceptions of climate and important outcomes (e.g., commitment to the organization, commitment to innovation, and the performance of innovative work behaviors). In addition, this work introduces a relatively new measure of the climate for innovation into the psychological literature.

Commitment to innovation is a very important outcome associated with worker perceptions of an organizational climate highly conducive to innovation. In this study, commitment is conceptualized according to Meyer and Herscovitch's (2001) and Herscovitch and Meyer's (2002) three-component model of commitment (affective, normative, and continuance) extended to multiple targets (commitment to the organization and commitment to innovation). This study is the first to measure commitment to innovation using an adaptation of this three-component model, and among the first to apply a new technique: latent profile analysis (LPA), which was applied to cluster organizational members according to their climate for innovation perceptions. Because LPA identifies individuals who share patterns of perception, its use accounts for individual variability.

Use of the attraction-selection-attrition (ASA) model (Schneider, 1987) allows researchers to describe the climate of an organization in terms of the attributes of its members, and to assess these attributes by climate measures. When organizational climate is examined in this manner, analysis of an individual's perception of climate may provide insight into the attributes of that individual and his/her observations of the situation. Although individuals in the same environment are likely to share similar perceptions of it, due to situational attributes, people with similar personalities in different environments are also likely to share perceptions of climate due to common characteristics that influence the way any environment is perceived. People dynamically interact with their environment (Terborg, 1981) in such a way that they are not only experiencing it, they are shaping it.

I begin this literature review by making a case for innovation as an important topic in the psychological literature. Next, I review of the concept of climate and present a summary of related literature (the focus of climate research, climate levels of analysis, and climate dimensionality) and a discussion of the concept of climate in terms of innovation and its outcomes. Next, I summarize various literature streams to emphasize the key points addressed in this study. I conclude the literature review with the presentation of a theoretical and methodological framework, eight research questions, and two explicit research hypotheses.

### **Innovation**

Although innovation receives significant attention in the academic and popular business management literatures, its definition is often ambiguous (Adams, Bessant, & Phelps, 2006). For this study, I defined innovation as the development and introduction of a new idea and the ability to transform that idea into a product, process, object, or service. Innovation is not only for research and for development functions; it can occur within all parts of an organization and be practiced by people at all levels of an organization as they ideate and change the way they perform work (Kanter, 1983).

Since the 1950s, the United States has led the world in scientific discovery and innovation (The Task Force on the Future of American Innovation, 2005). As much as 50% of U.S. business revenues are the results of new products and services (Mechling, 1995). Nevertheless, in the highly competitive and fast-moving global economy, U.S. innovative dominance is no longer a certainty. New research into the psychology of innovative

behavior in the workplace might provide a useful link between the business literature and work-world experiences. It is important to consider innovation in the psychological literature to assure its currency and utility.

Small businesses (fewer than 500 employees) create a significant number of new products and services and produce as many as 14 times more patents per employee than large businesses do (Leebaert, 2006). The patents produced by small businesses are twice as likely to be among the top 1% of patents cited by other researchers, which indicates that they are highly significant. In addition, small businesses employ 39% more scientists, engineers, and information technology (IT) workers compared to large businesses. Small businesses have other advantages and distinctive features as well: (a) they collaborate more openly to create new business partnerships and alliances; (b) they are more diverse, providing more opportunities for women and ethnic minorities; (c) they are more flexible and adaptable to changing economic conditions; (d) they account for 45% of U.S. technology spending; (e) they are more likely to deploy flexible production techniques; and (f) they offer improved job satisfaction and increased autonomy to their employees (Leebaert, 2006).

Large businesses are also innovating, of course, and taking a variety of approaches. Gillette spends millions of dollars globally each year on R&D and has set a goal of generating 40% of its revenues from new products (Center for Management Research, 2003). Its intensive R&D investments and strategy that involves developing product extensions have been largely successful for Gillette, which clearly views innovation as important and even launched an “Innovation is Gillette” marketing campaign. Nonetheless, R&D expenditures in an individual corporation or even across an industry are an insufficient measure to describe how and why innovation happens.

Another, wider model for innovation in a large company is seen at Proctor and Gamble (P&G), whose “Connect and Develop” program aims to build collaborative relationships and create partnerships with individuals and small businesses. Gillette’s approach to innovation involves increasing R&D expenditures; making incremental product improvements; and forming clear, challenging new product revenue goals. P&G has altered its business operations dramatically to foster collaborations that can result in innovative products and services.

As the U.S. economy becomes more knowledge-based and faces increased competition and an accelerated pace of change, it is a matter of survival for innovation to become a stronger area of focus for businesses both large and small (Adams, Bessant, & Phelps, 2006; Dougherty, 1996). Dougherty (1996) noted that despite the considerable attention paid to innovation in the industrial and management literatures, organizations—and in particular large organizations—do not innovate effectively. Believing that the flexibility and collaboration characteristic of small businesses may come naturally to them, some large businesses are attempting to foster situations that will allow them to capture some of the innovation advantages of small businesses. The P&G model, for example, is similar to a small business model: it involves collaboration, the open sharing of ideas, flexibility, empowerment, and rewards for innovation. Despite real differences in implementation, both small businesses and large business, (P&G, and Gillette being examples of the latter), seek to create environments that promote innovation. One could say that P&G as well as the general model for small businesses offer unique psychological climates—climates for innovation—that make innovation more likely to occur.

In order to address climates for innovation in detail, it is important to first explore the concept of climate itself. Specifically, the climate for innovation concept is a derivative of the “climate for something” approach (Schneider & Reichers, 1983) in the psychological climate literature. The more general climate construct, however, has a long history related to investigating the general influence of the environment, and in particular the influence of organizational systems, on individual behavior (Denison, 1996). In the sections that follow, I review several interdependent streams of the climate research literature, including the focus of climate research, the appropriate level of analysis in climate research, and the dimensionality of the climate construct. Despite its history, climate research still contains important, unresolved issues that are relevant to climate for innovation research.

### **Climate Focus**

Researchers have debated extensively about whether climate research should focus on organizations’ objective characteristics or the subjective interpretations of those characteristics by organization members (Denison, 1996). Guion (1973) eloquently compared the climate concept to “wind chill,” describing the latter as

the subjective interpretation of two objective events (wind speed and temperature) and concluding that the combination and interaction of objective characteristics and subjective interpretations is likely the truly important characteristic. In fact, the frequent use of survey methods by psychological researchers to collect climate data (Denison, 1996) implies their general satisfaction with the use of subjective interpretations.

The “structural approach” to climate research proposes that the characteristics of the organization, for example its structure and policies, affect individual perceptions of climate (Schneider & Reichers, 1983). From this perspective, the organizational environment shapes member perceptions of climate. James and his colleagues (James, Choi, Chia-Huei, McNeil, Minton, Wright, & Kim, 2007; James & James, 1989) described the importance of description and evaluation in assessments of climate but also noted that individuals’ description of climate does not occur in the absence of their interpretations of its value. Inherent in this observation is the idea that an individual’s values are part of the assessment of climate.

Schneider and his colleagues made notable contributions to climate research through the development and testing of the attraction-selection-attrition (ASA) model. Lewin’s (1951) classic field theory postulates that behavior is a function of a person in an environment, expressed as  $B = f(P,E)$ . In a seminal article that modified Lewin’s field theory, Schneider (1987) stated that behavior is not a function of a person in environment; instead, the environment is a function of the people behaving in it, or  $E = f(P,B)$ . Lewin, who posited that behavior is a function of people in an environment, places great emphasis on the importance of the environment in determining behavior. In contrast to field theory, Schneider’s proposition that people *are* the environment emphasizes the roles of people and their personalities, tendencies, and behaviors in creating and shaping environments. This idea led to the development of the attraction-selection-attrition (ASA) model, which states that: (a) people are attracted to and self-select into organizations based on organizational characteristics that are similar to their own personal characteristics; (b) organizations select people with personalities or tendencies similar to those inherent to the organization; and (c) if people do not “fit” the organization, they leave it by one means or another (Schneider, 1987).

The ASA model proposes that individuals are attracted to, are trying to find, and are selected into organizations based on their personal attributes, which means that the climate is defined by the attributes of its

individual members. In other words, selection and attrition procedures reproduce and reinforce climate. Similar types of people self-select into an organization, and organizational incumbents select new members viewed as similar in terms of their attributes, values, and other characteristics. Once in an organization, individuals stay or leave based on conditions of person-organization congruence. According to Bretz, Ash, and Dreher (1989), ASA predicts that organizations become more homogenous over time, and are therefore less able to change, or to respond to threats or opportunities in the environment. Alternately, homogeneity might provide the steadiness an organization needs in order to resist reaction or, more important, overreaction to insignificant, transient, or superficial turbulence within its environment. This steadiness may allow the organization to focus on innovation or other processes critical to its success.

Schneider's first proposition, relating to attraction and selection of people into organizations based on congruence of characteristics, may obscure other important choices people make. Although ASA is based in part on research and thinking about vocational choice (Holland, 1985; Super, 1953), it is possible that person-vocation congruence is more critical to individuals than person-organization congruence. Functional units within organizations, such as manufacturing or sales, are likely to display distinguishable sets of attributes because the people who pursue manufacturing and sales occupations do so based on their individual attributes, and in turn those attributes correspond to characteristics of the occupation and its existing members. A logical inference is that the organization as a whole might not be the only or best unit of analysis.

Although Schneider worded his third proposition strongly, it is equally clear that some people who do not "fit" an organization remain with it. Schneider's proposition assumes that an individual has the option to either stay or leave and that either the individual or the organization recognizes the "misfit." He also assumes that other factors do not interfere with the attrition process. For example, in order to save money companies may enact human resource practices that encourage early retirement, effectively enticing workers to leave the company when they otherwise would not do so. Alternately, companies may want to retain the tacit knowledge of older workers by offering them financial incentives to remain when they otherwise would retire.

According to ASA, climate *is* the attribute of an organization's individual members, and therefore measures of climate are proxy attribute measures. Therefore, responses to survey measures of climate provide

simultaneous insight into both the respondent's individual psychological reaction to the environment he/she observes, of which the respondent is a part, and also into the environment to which the respondent contributes. The total perception of environment comprises the combination and/or interaction of situational and dispositional factors. For example, employees in the same environment are more likely to respond to climate measures similarly, and the ASA process will cause employees in the same environment, work group, functional unit, and organization to become more similar over time. James and his colleagues suggested that employees with similar personalities, tendencies, or values are more likely to respond to climate measures similarly (James & James, 1989; James, et al., 2007).

The ASA model suggests the possibility of aggregating individual perceptions of climate based on shared environment, which can represent both situational and individual difference factors. Although ASA predicts greater homogeneity in work groups, functional units, and organizations over time, it specifies neither that those are the only meaningful groupings of people in an organization nor precludes, in the absence of a shared situation, grouping people based on individual differences. This point leads directly to the next major stream of research in climate: levels of analysis. More specifically, it enables examination of which level of analysis (i.e., individual, group, and organization) is appropriate for climate research.

### **Climate and Levels of Analysis**

There are several different points of view on the appropriate level of analysis. *Psychological climate*, defined as an individual, psychological construct, is dominant in the literature (e.g., Burke, Borucki, & Kaufman, 2002; Florin, Giamartino, Kenny, & Wandersman, 1990; Glick, 1985; James et al., 2007; Joyce, & Slocum, 1984; Parker, Baltes, Young, Huff, Altmann, Lacost, & Roberts, 2003; Schneider, & Brief, 1996; Schneider, Wheeler, & Cox, 1992). When the unit of theory is the individual, psychological climate is the most common conceptualization. According to James (1982), "the constructs of interest in climate measurement are intrinsically psychological ... it is axiomatic that the unit of theory be the individual" (p. 220). Although many researchers have concluded that the individual is the appropriate level of analysis for climate research, many also claim that at a higher level of analysis, aggregations of psychological climate may explain phenomena such as work unit or organizational performance (James, 1982). Nonetheless, as indicated throughout this section,

climate perceptual agreement among employees in the same organizations or work groups is often not sufficiently high to justify aggregation (Glick, 1985; James, 1982).

Another unit of climate analysis is *organizational climate* (Argyris, 1958; Glick, 1985). Researchers and practitioners who use this perspective treat climate as an organization-level construct and operationally define it as the average psychological climate, assuming an appropriate level of individual agreement. The absence of agreement at the organizational level is an indication that the climate construct does not exist there (Glick, 1985). The organizational perspective essentially obscures or dismisses the individual and the variability among individuals within organizations.

A third approach, which postulates climate at the *sub-group* level (Hellriegel & Slocum, 1974; Powell & Butterfield, 1978), contends that climate analysis may be undertaken at the individual, group, and organizational levels, depending on the chosen theoretical underpinning or specific constructs of interest. Glick (1985), who agreed that climate research at the individual, group, and organizational level is appropriate, advocated the use of multilevel modeling techniques to analyze resultant data. Clearly, various perspectives on climate analysis level can be complementary or in conflict. The rest of this section elaborates on such similarities and differences in an attempt to resolve them in terms of the present research.

Nord and Fox (1996) observed the research trend of focusing more on context than individuals, and particularly, the dynamic interactions between people and contexts. Although the individual-level psychological climate construct is dominant in the psychological literature, researchers and practitioners seldom restrict their attention to individual-level phenomena. Instead they tend to aggregate psychological climate data to higher levels according to the organizational hierarchy, such as the work unit or organization (e.g., James et al., 2007), and disregard individual variability. Findings at one level of analysis should have implications for other levels of analysis (Nord & Fox, 1996). However, the aggregation of individual level data to higher levels represents a significant leap that complicates both theory and methodology and provides two related issues to ponder: Is aggregation to formal and hierarchically arranged groups theoretically and methodologically sound? Likewise, to what level or how should aggregation of climate or other attitudinal data occur?



According to the structural approach, organizational characteristics such as mission, reporting relationships, or policies affect climate perceptions (Schneider & Reichers, 1983). The basic justification for the aggregation of climate data from this perspective is the belief that shared environments or experiences in the organization lead to shared perceptions of organizational climate. At each increase in hierarchical level (i.e., team, work group, department, business unit, organization), data can be aggregated. In the absence of measures of agreement, however, researchers and practitioners should not aggregate climate data to a higher level.

Although it has become relatively common practice to measure agreement before aggregating individual-level climate data to higher levels, the measurement of agreement is in itself problematic. Climate research suffers from findings of low interrater agreement and reliability (Glick, 1985). James (1982) examined 13 published studies and found that individual perceptual agreement, measured by intraclass correlation coefficients, ranged from  $ICC = 0.00$  to  $0.50$ , with a median value of  $ICC = .13$ . In the absence of agreement, aggregation to the level of work group, functional or business unit, or organization cannot be justified. Schneider and Reichers (1983) pointed out that in many studies, work groups in the same organization do not agree on the organization's climate. Accordingly, they suggested that members of work groups develop shared meaning at the work group level because of their frequent interaction. From these results, one could conclude that social interaction is a basis for the development of shared meaning and shared perceptions of climate. Rather than conceptualizing climate as *something* that is communicated from the top down within an organization and thereby justifying aggregation of climate scores up to higher levels, it appears that climate may develop horizontally as individuals within smaller organizational segments interact with each other and create their own "micro-climates" (Schneider & Reichers, 1983).

From these few examples, it can be inferred that aggregation to levels corresponding to formal group or organization boundaries is not theoretically or methodologically sound in all cases, particularly if researchers simply average psychological climate to operationalize organizational or group climate. Findings of low interrater reliability and low interrater agreement, as well as the requirement to make conceptual leaps, make the practice of aggregating individual level climate data to higher levels problematic (Glick, 1985; Joyce & Slocum,

1984). Methodologically, the agreement statistics for climate studies (James, 1982) suggest that in many cases, agreement scores may be too low for aggregation of climate data.

There is theoretical support for the idea that sharing a work environment is not the only influence on one's perception of climate; instead, one's attributes, personality, or values may also influence these perceptions (James & James, 1989; James, et al., 2007; Schneider, 1987). Although it is probably true that group and organizational factors influence individually reported perceptions of climate, and that those perceptions have influence at the organizational, group, and individual levels, it is not clear that changes in the work environment will necessarily be equally noticeable, important, or desirable to all people in accordance with formal organizational boundaries. Shared perceptions may be due to structural features of the organization, informal relationships in the organization, individual differences, or combinations of these factors. Simple aggregation to the work group and organizational levels seems inadequate to represent this complexity.

Schneider and Reichers (1983) advocated use of clustering techniques in the study of climate. Mathisen and Einarsen (2004) and Joyce and Slocum (1984) suggested that, because individuals fulfill multiple organizational roles that are not always reflected by organizational boundaries, artificial organizational boundaries should not be the sole basis for aggregation. Young and Parker (1999) demonstrated this empirically when they found that perceptions of the work environment related to interactions at work rather than formal work department membership. This finding supports the view that social interaction is a basis for the development of shared meaning (Schneider & Reichers, 1983).

Joyce and Slocum (1984) and James (1982) contended that because psychological climate is an individual perception, the shared perception of climate should not depend on artificial units of analysis such as organization, business unit, sub-unit, or work group. Therefore, Joyce and Slocum used a clustering technique as the basis for aggregation of climate scores, and used perceptual agreement as a criterion for aggregation. They termed the multiple climates that resulted from this approach "collective climates" and interpreted them as representations of learned environments. Within each organization that they investigated, Joyce and Slocum (1984) found different sub-climates that demonstrated high reliability: sub-climate clusters predicted individual satisfaction and performance. Joyce and Slocum (1984) were also able to predict important organizational

outcomes according to cluster after grouping people by means of a traditional clustering technique. By doing so, they demonstrated that shared perceptions of climate are not necessarily tied to formal work groups and that other models of aggregation can produce meaningful results. This important contribution suggests the potential effectiveness of the aggregation approach employed in the present research.

Payne (1990), however, argued that collective climates are not meaningful in the absence of correspondence to formal organizational roles. He contended that non-corresponding clusters of individuals in an organization only demonstrate that clustering techniques work and argued that such clusters might arise from shared personalities, values, or interests, rather than from the organizational environment or from climate as he defined it. Payne's logic suggests that the presence of collective climates that do not correspond to formal organizational groups undermines the usefulness of identifying collective climates with clustering techniques. To establish this point further, Patterson, Payne and West (1996) used a clustering technique to compare cluster membership with membership in formal organizational groups. Not only did they find that clusters were unrelated to formal organizational structure, they commented that the resultant clusters in their study were "remarkable only in the diversity of the different organization segments (regions, construction sites, and offices) to which they belonged" (p. 1683). However, their sample was small ( $n = 133$ ) and the number of clusters they identified was relatively large ( $n = 10$ ).

Even if perceptions of climate result from a non-organizational cause, this finding does not necessarily negate the use of clusters to interpret organizational data. In other words, it may not matter why people think similarly. The fact remains that they do think similarly and therefore clustering may be useful for interpreting climate data. However, the views of Payne and his colleagues are important, particularly (as is often the case) when the goal of practice or research is to characterize group or organizational climates in terms of the average psychological climate. Other goals, however, are also possible. Groups, including organizations, may be viewed as *salad bowls* instead of *melting pots*. From this perspective, the usefulness of clustering group members based on their perceptions is particularly promising and may indeed be a more correct way of characterizing organizations and their respective climates. One could describe an organization's climate as an aggregation, or

*macro-climate*, in terms of the presence and dispersion of various perceptions of climate, i.e. *micro-climates*, throughout the organization.

As reviewed in the preceding section, researchers have conceptualized climate as the objective characteristics of an organization, as the subjective interpretation of objective environmental or organizational characteristics, and as a reflection of the personal attributes of the members in an organization. The research discussed in this section most often treats climate as an individual or psychological level concept but also aggregates climate data to higher levels of analysis in accordance with organizational boundaries, guided by agreement statistics. One issue with that type of aggregation, however, is that measures of agreement are often not high enough to justify it. With this in mind, some researchers have used clustering techniques as an alternative. Rather than aggregating to groups that adhere to formal organizational boundaries, it would appear that informal group membership or social interaction may represent a more meaningful and justifiable way to cluster individuals into groups that share perceptual agreement. In addition, the meaningfulness of these groups may extend beyond demonstrating perceptual agreement of climate; this type of aggregation may allow differential predictions of important criteria from climate. To date, the literature does not show resolution of these issues. In addition, a third major issue remains: the dimensionality of climate, specifically the dimensions of the climate construct and how they relate to important criteria.

### **Climate Dimensionality**

Despite a lengthy history of climate research, researchers do not consistently define or measure climate in the literature. Instead, they debate which associated constructs are important as well as whether climate constructs are unique to climate research or overlap with existing constructs in the broader psychological literature. In work that represents much of the climate dimensionality literature, James and James (1989) reviewed the dimensionality of the general psychological climate construct and proposed a model based upon four first-order climate factors and only one second-order factor ( $PC_g$ ). The four first-order climate factors are: (a) role stress and lack of harmony; (b) job challenge and autonomy; (c) leadership facilitation and support; and (d) work-group cooperation, friendliness, and warmth. The role stress and lack of harmony factor includes concepts such as role ambiguity, role conflict, role overload, subunit conflict, lack of organizational

identification, and lack of management concern and awareness. The job challenge and autonomy factor involves job challenge and variety, job autonomy, and job importance. The leadership facilitation and support factor involves concepts such as leader trust and support, leader goal facilitation, leader interaction facilitation, psychological influence, and hierarchical influence. Finally, the work-group cooperation, friendliness, and warmth factor involves concepts such as work-group cooperation, work-group friendliness and warmth, and responsibility for effectiveness (James & James, 1989).

Researchers have criticized the climate construct for conceptually overlapping with other constructs in the psychological literature, including:

- structure, technology, formalization (James & Jones, 1974);
- satisfaction (Guion, 1973; Hellriegel & Slocum, 1974; Johannesson, 1973);
- psychological distance (Payne & Mansfield, 1973);
- managerial function (Schneider, Parkington, & Buxton, 1980);
- leader facilitation and support (James & Jones, 1974);
- managerial trust and consideration (Gavin & Howe, 1975);
- open-mindedness (Payne & Mansfield, 1973);
- superior and subordinate information (Bass, Valenzi, Farrow, & Solomon, 1975);
- warmth (Downey, Hellriegel, & Slocum, 1975);
- communication flow (Drexler, 1977);
- competence (Lawler, Hall & Oldham 1974);
- risk orientation (Lawler, Hall & Oldham 1974);
- courtesy (Schneider, Parkington & Buxton, 1980); and
- overall quality (Schneider, Parkington & Buxton, 1980).

The preceding list of climate dimensions represents a small sample of other constructs in the psychological literature that overlap conceptually with climate constructs.

A proposed solution to this issue of construct overlap is to use only criterion-related climate dimensions (Jones & James, 1979; Joyce & Slocum, 1984; Schneider, 1975); that is, to identify and limit

climate dimensions on any one measure within the scope of the criteria of interest. Similarly, Bartram (2005) noted, “Researchers have asked questions like, ‘What does instrument X predict?’...We should be asking ‘How can we best predict Y?’ where Y is some meaningful and important aspect of organizational behavior” (p. 1185). Suggesting that researchers shift attention from predictors to criteria, Schneider and Reichers (1983) called the criterion-referencing of climate constructs the “climates for something” approach and contended that work settings have different climates for specific things such as safety, service, production, security, and quality. Delineation of climates for safety (e.g., Mearns, Whitaker, & Flin, 2003), climates for service (e.g., de Jong, Ruyter, & Lemmink, 2004; Dietz, Pugh, & Wiley, 2004), climates for creativity or innovation (e.g., Ekvall, 1996), and climates for teams (e.g., Anderson & West, 1998) are recent examples of this approach. Criterion-referencing provides focus for the selection of climate dimensions, while climate remains the construct of interest (Glick, 1985).

The discussion of the literature up to this point has largely focused on the origin, level of analysis, and dimensionality of climate. Bartram’s (2005) point, however, is worth further consideration due to its focus on important outcomes such as innovation, which are likely to be useful for identifying and validating important predictor-criterion relationships. Criterion-referencing of climate surveys may also provide valuable face validity for climate surveys to organization managers and incumbents, who are more likely to be interested in criteria than in predictors. Scott and Bruce (1994) noted that the dimensions of general climate measures are not always relevant to the criteria of interest. Another important link between climate and innovation occurs within the context of the “climate for something” approach, one of which is the climate for innovation (Ekvall, 1996). The shift to using a criterion-referenced climate for innovation measure contextualizes the climate construct and increases the likelihood of identifying predictor-criterion relationships. In the next section, I present research related to the dimensionality of the climate for innovation and relationships between the climate for innovation to related organizational outcomes.

### **Climate for Innovation**

Researchers pay some attention to climate for creativity and climate for innovation in the psychological literature. Whereas researchers often use climate for creativity to describe situations that promote

the creation of new ideas, they use climate for innovation to describe situations that promote the creation and implementation of new ideas (Janssen, 2003; Mathisen & Einarsen, 2004). Climate for innovation subsumes climate for creativity. Further research is needed about the origin and dimensionality of climate for innovation and the relationships between climate for innovation and important innovation and organizational outcomes.

As noted earlier, I defined innovation as the development and introduction of a new idea and the ability to transform that idea into a product, process, object, or service. Kwaśniewska & Necka (2004) defined climate for innovation as a "... situation in which the generation, consideration and use of new products, services, and ways of functioning are promoted" (p. 188). Much like the dimensions found in the climate literature, the important attributes to consider in a climate for innovation are not consistent in the literature and demonstrate construct overlap. As in the general climate literature, climate for innovation researchers developed several competing theoretical models and measurement instruments to reflect conceptual differences and to meet their particular research interests or needs.

Mathisen and Einarsen (2004) analyzed four of the major theoretical models and instruments designed to assess climate for creativity and climate for innovation and concluded that there are more similarities than differences in the conceptual areas each attempts to address. They did find, however, four major areas of agreement among the models they reviewed. First, the models attempt to explain how work environments promote or inhibit innovation and creativity, though all place greater emphasis on promotion over inhibition. Second, the models include the idea of "support" for innovation (Amabile, Conti, Coon, Lazenby, & Herron, 1996; Ekvall, 1996; Siegel & Kaemmerer, 1978; West & Anderson, 1996). Third, the models reflect the notions of shared goals, ownership of ideas, or commitment (Siegel & Kaemmerer, 1978). Fourth, other theoretical dimensions occur frequently among the models, including the open exchange of ideas, open relationships among peers and leader/subordinates, freedom, challenge, trust, and collaboration (Amabile et al., 1996; Ekvall, 1996). All of these factors prove useful in the prediction of innovation or creativity at the individual or team level (Mathisen & Einarsen, 2004).

In contrast to these relatively complex models of climate for innovation, Scott and Bruce (1994) reduced the climate for innovation to only two dimensions: support for innovation and resource supply. They

defined support for innovation as organizational support for members to work independently and pursue new ideas. They further defined resource supply as the adequate supply of resources such as equipment, facilities, and time. They selected these dimensions based on Abbey and Dickson's (1983) research that used a general climate measure to determine that these two dimensions predicted innovation outcomes. Although Scott and Bruce did not replicate Abbey and Dickson's findings with regard to resource supply, they did demonstrate that support for innovation predicts innovation outcomes.

Leebaert (2006) confirmed the broad categories in which innovation is defined: investment in research and development, success of new products, revenues from new products and services, and the number and significance of the patents produced. These group- or organizational-level variables are not appropriate outcomes for the psychological climate for innovation concept directly, however. In the absence of measures of agreement to justify aggregation of climate for innovation data, research should focus on individual-level outcomes, particularly commitment and innovative work behavior.

### **Climate for Innovation Outcomes**

**Innovative Work Behavior (IWB).** IWB is the main criterion in the criterion-based climate for innovation approach. Scott and Bruce (1994) described IWB as a discontinuous process involving problem recognition, the generation of ideas (novel ideas or adopted ideas), the seeking of sponsorship for ideas, coalition building, and the implementation or production of ideas. Janssen (2000) defined IWB as "...the intentional creation, introduction and application of ideas within a work role, group or organization, in order to benefit role performance, the group, or the organization" (p. 288). Although these and other definitions differ somewhat, the literature also reflects agreement about some specific components of IWB. At the individual level, IWB involves creative behaviors such as the recognizing problems and generating ideas, as well as implementation behaviors such as promoting and realizing ideas (Dorenbosch, van Engen, & Verhagen, 2005). This two-dimensional conceptualization of innovative work behavior is relatively consistent in the literature (Dorenbosch, van Engen, & Verhagen, 2005; Janssen, 2000; Kanter, 1988; Scott & Bruce, 1994).

Scott and Bruce (1994) successfully predicted IWB from support for innovation, but not from resource supply, a finding that differs from suggestions found in previous literature (e.g., Abbey & Dickson, 1983).



Individual IWB should predict organizational-level innovation criteria of interest, such as the number of patents and their importance or significance, as well as the successful implementation of new organizational practices or business models. Empirical evidence is not yet apparent.

**Commitment.** Commitment is another variable related to the dimensionality of climate for innovation (Dougherty, 1996; Mathisen & Einarsen, 2004). Some models of climate for innovation include a commitment dimension (e.g., Amabile et al., 1996) while others use commitment as an antecedent (e.g., Dougherty, 1996), intervening variable (e.g., James & Jones, 1974), or criterion (e.g., Dickson, Smith, Grojean, & Ehrhart, 2001) in their models. Similarly, Kontogiorghe and Bryant (2004) found employee commitment to be dependent on the extent to which:

- (a) the employee functions in an environment that has few bureaucratic barriers to getting the job done properly;
- (b) people on one step of the operation regard the people in the next step of the operation as their customers and try to meet their needs;
- (c) the employee is expected to use newly learned skills and knowledge learned in training;
- (d) the employee receives praise and recognition when applying new skills and knowledge on the job;
- (e) the employee is well rewarded for his or her learning;
- (f) innovators get ahead in the organization;
- (g) there is an organization focus on process improvement;
- (h) the employee is a member of a self-directed work team;
- (i) the amount of output by peers exceeds expectations;
- (j) the employee is given the opportunity to do what he or she does best;
- (k) peer output is received in a timely fashion; and
- (1) the job requires skill variety. (p. 5)

Though not explicitly stated, the situation described in this study seems to constitute a climate for innovation; that is, an environment in which novelty is encouraged, employees find work meaningful and controllable,

learning is incorporated into work, innovation and process improvements are implemented, and a focus external to the company is fostered.

Meyer, Srinivas, Lal, & Topolnytsky (2007) noted that change theorists accord commitment a prominent place in their models of implementation. Herscovitch & Meyer (2002) demonstrated that commitment is an important antecedent to organizational change. A study in the health care industry by McNeese-Smith (1996) demonstrated that employees who perceived their companies to value change and new technology had higher levels of organizational commitment.

The relationship found by Kontoghiorghes and Bryant (2004) between situations that enable innovation and commitment is significant. Commitment to the organization is important to companies for a variety of reasons, and particularly to high technology companies and companies that rely heavily on innovation. In the absence of commitment, turnover wastes valuable resources and the time and money required to train and socialize new employees is high. Although highly committed employees are likely to remain with the organization and to exert greater effort on behalf of the organization, the conceptualization of commitment in the literature is inconsistent. Meyer and his colleagues have developed a particularly compelling framework of commitment (Allen & Meyer, 1990; Herscovitch, & Meyer, 2002; Meyer, Becker, & Vandenberghe, 2004; Meyer & Herscovitch, 2001; Meyer, Srinivas, Lal and Topolnytsky, 2007).

Allen and Meyer (1990) described a three-component model of commitment to the organization that includes affective, normative, and continuance (ANC). Affective commitment is an employee's emotional attachment to, identification with, and involvement in the organization. Continuance commitment is an employee's perceived cost of leaving the organization versus the perceived benefit of continuing an organizational relationship. Normative commitment is an employee's feelings of obligation to the organization. Consistent with theory, the strongest relationships between commitment and important outcomes such as job performance, organizational citizenship behavior (OCB), and attendance are found for affective commitment, followed closely by normative commitment (Meyer, Becker, & Vandenberghe, 2004).

Although the organization is the most common target of commitment in the literature, Herscovitch & Meyer (2002) discuss the differences between commitment to the organization and other targets (i.e., teams,

supervisors, coworkers). They advocate the use of commitment measures that apply the three-component (ANC) model to targets that are within or are associated with the organization. For example, when Meyer, Srinivas, Lal and Topolnytsky (2007) investigated the pattern of relationships on the three types of commitment (ANC) to two targets (the organization and an organizational change initiative) they concluded that commitment to the change initiative accounted for more variance in support for the change than commitment to the organization did. In addition, they concluded that ANC commitment predicted compliance with requirements for the organizational change initiative, although they also observed that higher levels of continuance commitment restricted employee behavior to compliance with only the minimum behavioral requirements. Showing that members of the organization hold different levels of different types of commitment to different targets enabled Meyer et al. (2007) to demonstrate that the complexity of commitments predicts organizational behavior of interest. They provided evidence that the three-component (ANC) model of commitment, contextualized to specific targets (such as organizational change initiatives), may expand understanding of the complex relationships between employees' commitment and behavior.

Ruppel and Harrington (2000) investigated innovative behavior and commitment to innovation as outcomes of a climate for ethical behavior. Using a three-item commitment to innovation scale and qualitative data, they found that ethical work climates characterized by high trust and communication predict innovative behavior and commitment to innovation. They concluded that individuals who perceive that their organization is good or ethical, perform better, innovate more, and demonstrate higher commitment to innovation.

Dougherty (1996) observed that organizational activities related to innovation (market-technology linking, organizing for creative problem solving, and monitoring and evaluation) require unusually high levels of commitment to the organization. In other words, for a company to innovate, individuals within it need to feel fully integrated with their work and also need to invest in their work with substantial time, energy, and attention. In the course of claiming that commitment is a problematic area for innovation, she described commitment as a tension between freedom and responsibility. This tension can be expressed from perspectives that are informed by individual differences or situational factors. From an individual difference perspective, individuals must be creative or independent to develop new ideas and must be responsible enough to see ideas

through the implementation stage. From a situational perspective, the organization must provide an environment that fosters creativity and independence and that requires accountability so that employee follow-through to implementation is assured.

Just as “climate for innovation” contextualizes climate, “commitment to innovation” contextualizes commitment and “innovative work behavior” contextualizes work behavior. Individuals who hold different perceptions of the climate for innovation are likely to demonstrate varying levels of commitment to innovation and to the organization in general. In addition, individuals who hold different perceptions of the climate for innovation are likely to demonstrate differences in innovative work behavior. Although I specify these relationships at the individual level of analysis, when agreement is sufficiently high to justify aggregation of climate perceptions, I expect these predictions to hold at the group or organization level also.

## **Conclusion**

In this literature review, I have identified outstanding issues and competing points of view related to: (a) the focus of climate research, (b) the level of analysis for climate research, (c) the dimensionality of climate, (d) climate as a criterion-referenced predictor, and (e) climate for innovation criteria. I briefly summarize these issues below and present my perspectives about them in relation to the current research study.

First, researchers continue to disagree about whether climate should focus on the objective characteristics of an environment, on the subjective interpretation of those characteristics, or on the attributes of group members within the environment. Most research on climate, however, relies on subjective interpretation of climate gathered by climate survey instruments. The present study is no different. Although I acknowledge the importance of describing objective characteristics of organizations, when survey methodology is employed, I believe the resultant data represents subjective interpretations. Unfortunately, the degree to which those subjective interpretations represent organizational characteristics or individual differences cannot be fully known.

Second, researchers disagree not only about the appropriate level of analysis for climate, but also about whether and about how to aggregate individual-level data. Researchers may conceptualize climate as an individual-, group-, or organization-level construct, although most conceptualize it at the psychological or

individual level. These differences complicate neither theory nor methodology; however, aggregation of climate perceptions does complicate both. Whereas some researchers argue that groups of people who share a meaningful perception of climate may not be bound by formal organizational boundaries, others argue that a group must correspond to formal organization boundaries if meaning is to be inferred for it. For this study, the important task is to determine how to group individuals in a meaningful way. The issue is not whether or not to aggregate climate data to the formal levels of group or organization, but rather whether or not groups that share climate perceptions do so *because* of those memberships. Aggregation to the group level, from the latter perspective, does not involve checking formal groups for agreement, but instead depends on recognizing group formation based on agreement, and then assessing whether situational and individual differences predict group membership.

Third, the dimensionality of climate remains problematic. In general, researchers agree that psychological climate is a second-order latent factor but disagree about which are the first-order latent factors. Many also lament the conceptual overlap in the psychological literature of many proposed first-order factors with other concepts. Criterion-referencing, which shifts focus from the taxonomy of climate dimensions to maximizing the prediction of climate outcomes, is one way to deal with the dimensionality of climate issue. The choice of criterion-referencing also addresses the issue of the meaningfulness of groups. In response to Payne and his colleagues, I take the position that the question of meaningfulness should be answered empirically. Instead of being limited to the formal structure of the organization, meaningfulness should be determined by the differential prediction of important criteria. It may be that unique sub-climates interact to create or define the larger organizational climates.

Fourth, the climate-for-innovation construct is a criterion-referenced psychological climate construct. Although there is some debate about the dimensionality of the climate for innovation, considerable evidence suggests it should predict innovation outcomes, such as innovative work behavior and commitment. Because it is a criterion-reference, climate for innovation should predict such outcomes more effectively than do more general climate constructs.

Finally, measuring innovation by group- or organization-level indicators may be inappropriate for the identification of individual-level predictors. Climate for innovation perceptions should combine to predict individual innovation outcomes such as commitment to the organization, commitment to innovation, and innovative work behavior. Although the literature still lacks an empirical demonstration, these individual-level outcomes should predict more commonly used group-level or organization-level criteria.

### **Theoretical and Methodological Framework and Implications**

**Theoretical Framework.** Wapner and Demick's (2000) articulation of person-in-environment psychology as "a holistic, developmental, systems-oriented perspective" (p. 25) has influenced my thinking about and interpretation of climate and its related literatures. The main ideas in person-in-environment psychology that I share and that relate to the present study are: (a) an organismic and transactional worldview, which emphasizes synthesis and wholeness of person-environment systems; (b) constructivist philosophy, in which reality is subject to perception and people actively and intentionally pursue goals; (c) use of the systems unit of analysis, in which individuals are conceptualized as systems, individuals in groups are systems, and so forth; (d) levels of analysis integration, in which functioning at one level of analysis relates to functioning at all other levels of analysis; and (e) methodological eclecticism (Wapner and Demick, 2000), which values all methods.

I also subscribe to complexity theory (Geyer, 2003), which recognizes that: (a) biological and organizational systems are complex and dynamic; (b) events are only partially predictable because they are caused by both orderly and nonorderly phenomena; and (c) systems have adaptive and emergent properties. Complexity theorists tend to favor modeling techniques and advocate for diversity in methods and interpretations. In light of these theoretical and philosophical underpinnings, for the current study, I chose a methodology that integrates the variable and pattern approaches to data analysis in order to address the climate for innovation issues examined herein. I explain what I mean by the terms "variable approach" and "pattern approach" in the next section.

**Methodological Framework and Implications.** Researchers using the variable approach specify, identify, define, and otherwise study variables across people or situations, and in relation to criteria (other

variables) of interest. This underlying premise offers a major advantage in the form of parsimony (Foti & Hauenstein, 2007). Most climate researchers have used the variable approach exclusively to address questions related to the dimensionality of climate, criterion-referencing of climate, climate for innovation criteria, and even levels of analysis. Regarding the latter, however, the variable approach often obscures individual variability by treating it as measurement error. Exclusive use of this approach therefore diminishes the importance of considering individual variation; such researchers tend to use linear or static models (Foti & Hauenstein, 2007) that also fail to represent the complexity in relationships.

The pattern approach, on the other hand, is person-centered. Individuals are treated holistically, as systems, and are the primary unit of analysis (Foti & Hauenstein, 2007). The main goal of using a pattern approach is to identify clusters, groups, or profiles of individuals and to study them over time. Researchers who use pattern approaches give attention to individual variability, interactions, complexity, dynamic relationships, and nonlinear relationships. By contrast, a researcher using the variable approach may assign a second-order climate score to each individual that represents an average of scores or a weighted average score across all climate dimensions.

In accordance with the systems and complexity ideas discussed above, the pattern approach is a modeling approach that allows for the possibility of emergent or adaptive characteristics of individuals or groups of individuals. Although researchers underutilize the pattern approach, it is a complement, not an alternative, to the variable approach. Patterns represent individuals by their positions on interacting variables. The pattern, in effect, becomes the variable used to predict criteria of interest.

Relevantly to the present study, Joyce and Slocum (1984) used a pattern approach when they clustered individuals based on their perceptions of climate and then used the climate perceptions to predict important organizational outcomes. They demonstrated both that shared perceptions of climate are not necessarily tied to formal work groups (exclusive variable approach) and that other models of aggregation (e.g., pattern approaches) can produce meaningful results.

In addition to traditional clustering techniques, latent profile analysis (LPA) techniques can be used to identify groups. LPA is a pattern approach that groups individuals based on profile similarity across variables,

such as climate for innovation perceptions. Unlike traditional clustering techniques, such as *k*-means or Ward's method, LPA is a model-based approach (Magdison & Vermunt, 2002). For model-based approaches, like LPA methods, the results for a sample are estimates for the population from which the sample was drawn. More practically, LPA methods allow researchers to generate probability-based classifications so that probability of class membership can be estimated for each case. Such estimates are not possible with traditional clustering techniques, because within them class membership is weighted by an indicator variable (where 0 = *nonmember* and 1 = *member*).

In addition, the statistical assumptions of LPA comport with common characteristics of survey data. Researchers can analyze data that fail to meet standard assumptions, such as multivariate normality, equal variances, and factor independence, without violating the stated assumptions of LPA. Researchers can also incorporate many types of variables into LPA models, including nominal, ordinal, or continuous data and mixed scale-types, and the data need not be standardized. Scaling and standardization of variables is an issue for traditional clustering techniques, so researchers must estimate the relationships of demographic data or other covariates after the fact using techniques such as discriminant analysis. Furthermore, using LPA researchers can classify cases and analyze covariate contributions to the classification using data from mixed-scale types (Magdison & Vermunt, 2002). LPA techniques make it possible to simultaneously conceptualize climate perceptions as an individual-level, complex phenomenon; to group individuals based on profile similarity; and to estimate the impact of situational and individual difference covariates.

I chose this methodology in order to address several issues in the climate literature that require exploration in a manner consistent with the foundations of both complexity theory and person-in-environment theory. Specifically, by choosing this methodology I was able to treat perceptions of innovation climate as individual-level, subjective interpretations of the environment as it is affected by individual differences and situational influences. The dimensionality and criterion-referencing of the climate for innovation construct are also preserved because this technique allows me to assess the meaningfulness and usefulness of various climate dimensions in terms of how well each dimension differentiates individuals and predicts innovation outcomes. I sought to group individuals based on agreement and, without completely disentangling joint or interactive



effects, to estimate the influence of individual differences and situational influence upon those groupings. Moreover, I wanted to know whether the group variable, identified on the basis of those joint and interactive effects, could predict important outcomes beyond the climate for innovation variables.

The list of possible situational and individual difference influences is extensive. I chose to examine company membership, functional unit membership, organizational level, and organizational tenure as covariates to LPA.

In the climate literature, company membership is the most common indicator of situation. Researchers expect climate perceptions to differ based on this indicator not only because it represents the situation but also because it is often the intended unit of analysis and explanation. In the present study, company membership appears as a demographic covariate treated as an individual indicator of situation and also as a joint indicator of situation in combination with three other demographic covariates yet to be described.

Functional unit membership is a demographic covariate that can provide information about the relative influence of situation and individual differences. Within an organization, this covariate represents a shared environment and thus is a situational influence. Researchers expect that the objective climates differ within a company and within a functional unit, and that such differences influence employees' perceptions of climate. Not only do people in a functional unit within a company share educational and training experiences, daily work experiences, and general roles, they also are more likely to interact regularly and work more closely together than members of an organization do in general. However, functional unit membership is also indicative of individual differences. People choose occupations and functional responsibilities that match their own tendencies and leave those that do not. People with similar likes and dislikes self-select into particular occupations or functional areas. Holland's (1985) work on vocational choice supports these notions. Functional unit membership across organizations reflects the influence of individual differences.

Level in the organizational hierarchy, also called organizational level, is another demographic covariate used in the present study. Like functional roles, organizational levels are selected and continued based on personal attributes and job congruence, reflecting individual differences. These characteristics may become particularly apparent when non-managers are compared to managers and executives. In general, executives and

managers tend to have more influence in the establishment, development, and interpretation of the meaningfulness of climate for other organizational members. Leaders enact practices that communicate climate to subordinates. For example, the supervisor or manager is intricately involved in the degree to which employees experience open communications within the organization.

The perspective of leaders differs from the perspective of followers for several reasons. As organizational level increases, climate perspective is increasingly related to factors involving subordinates; as organizational level decreases, climate perspective is increasingly related to factors involving superiors. Because of the occupational and perspective issues, across companies organizational level should reflect an individual difference variable. However, within a company, organizational level also reflects a shared environment or a situational influence on perceptions of climate. By this, I mean that executives, managers, and non-managers within a company are likely to share experiences and environments that influence their perceptions of climate.

Organizational tenure is an important variable in the examination of climate, particularly from the perspective of the ASA framework (Schneider, 1987). According to this model, although both new and seasoned members of an organization have been attracted to and selected into an organization, those with less tenure have not had as much time to leave the organization for any reason. Therefore, those with longer tenure in an organization are more likely to agree with one another in terms of their perceptions of climate. Within an organization, and in accordance with the homogeneity of variance hypothesis, it is likely that the variability in climate perceptions would decrease with increased tenure, because tenure limits the degree to which individuals have shared work experiences and historical knowledge of the organization. Clearly organizational tenure within an organization represents a situational influence.

Although Schneider's proposition about ASA and tenure applies only to within-organization comparisons, findings of cross-organizational, tenure-linked homogeneity of variance may be due to individual differences. For example, since tenure can be a proxy variable for age and generational differences (Pond & Geyer, 1991), tenure may contribute to differences in perceptions of climate.

The four demographic covariates considered in the present research that may shed light on the relative influence of situational factors include: (a) company membership, (b) within-company functional unit membership, (c) within-company organizational level, and (d) within-company organizational tenure. The demographic covariates considered in the present research that may inform the relative influence of individual differences include: (a) across-company functional unit membership, (b) across-company organizational level, and (c) across-company organizational tenure.

Consistent with the findings of previous climate and innovation climate research, each climate for innovation dimension should predict important organizational outcomes such as commitment and innovative work behavior (variable approach). The nature and strength of these relationships are potentially affected by shared environments, shared experiences, and other unobserved characteristics such as personality or other personal attributes that will be represented by latent class membership (pattern approach). Individuals are grouped and described according to their climate perceptions using LPA (pattern approach). The meaningfulness of the groups derived by LPA is evidenced by the way important organizational outcomes are associated with the groups (variable approach).

### **Research Questions and Hypotheses**

In the present study, I sought to answer several research questions related to the grouping of individuals based on their climate for innovation perceptions and to the relative contributions of several situational and individual differences covariates to those groupings. In addition, I made two explicit hypotheses related to the homogeneity of variance hypothesis expressed in Schneider's ASA theory (1987).

**Research Questions (RQs).** I posed eight formal research questions:

*RQ 1:* Which latent profiles of climate for innovation perceptions are used to distinguish classes or groups of individuals?

*RQ 2:* Which demographic covariates contribute most to the formation and identification of latent profiles for climate (e.g., company, functional unit membership, organizational level, and organizational tenure)?

- RQ 3:* To what extent are perceptions of the climate for innovation influenced by situational or environmental factors (e.g., company membership, functional unit membership within company, organizational level within company, and organizational tenure within company)?
- RQ 4:* To what extent are perceptions of the climate for innovation influenced by individual differences (e.g., functional unit membership across companies, organizational level across companies, and organizational tenure across companies)?
- RQ 5:* If both situational and individual difference variables are important to perceptions of climate, is one type of variable dominant?
- RQ 6:* Do profiles of climate for innovation perceptions predict affective, normative, and continuance commitment to the organization?
- RQ 7:* Do profiles of climate for innovation perceptions predict affective, normative, and continuance commitment to innovation?
- RQ 8:* Do profiles of climate for innovation perceptions predict creative and implementation work behaviors?

**Research Hypotheses (RHs).** I made two research hypotheses, based on the homogeneity hypothesis associated with the ASA model (Schneider, 1987):

- RH1:* Within company groups defined by functional unit membership, the variability of climate for innovation perceptions will be negatively related to organizational tenure.
- RH2:* Within an individual company, the variability of climate for innovation perceptions will be negatively related to organizational tenure.

## **Method**

### **Participants**

I used an archival dataset from the Center for Innovation Management Studies (CIMS) to test the research questions and hypotheses posed. This dataset ( $N = 1891$ ) contains five independent samples of participants drawn from four companies. Three companies were each surveyed once, and the fourth company was independently surveyed twice. Each sample was a convenience sample, and no information about response

rates was available. Each of the four organizations surveyed is a global, high-technology firm, and each is a leader in its industry.

Company A ( $n = 406$ ) has 30,000 employees worldwide and is involved in the manufacture of pharmaceuticals, chemicals, and plastics. Company B ( $n = 491$ ) has 14,000 employees worldwide and is primarily involved in supplying chemicals to Original Equipment Manufacturers (OEMs) in consumer products industries. Company C ( $n = 303$ ) has 10,000 employees and is primarily involved in the manufacture of textiles and chemicals. Company D has 65,000 employees worldwide and is primarily involved in aluminum and other packaging. Company D was sampled independently on two occasions. On the first ( $n = 308$ ), only the predictor and demographic items were surveyed. On the second ( $n = 383$ ), predictor, demographic, and criterion data were collected.

The data gathered from all four companies were used in the exploratory section of this study ( $N = 1891$ ). For the predictive analyses, I only used the data from Company D ( $n = 383$ ) that contained both predictor and criterion data, and hereafter referred to as the target sample. All measures used in this study are presented in Appendix A.

## Measures

**Climate for Innovation.** The Innovation-Capacity Climate Survey (ICCS; Aiman-Smith, Goodrich, Roberts, & Scinta, 2005) is an instrument that was jointly developed by a professional industrial organization and a group of academic researchers to measure perceptions of organizational cultural dimensions that relate to innovation in companies. The researchers drew the ICCS dimensions from the climate, culture, and innovation literatures, wrote new items to assess those dimensions, and then tested the items with several pilot samples. They also conducted exploratory factor analysis to reduce the number of items and factors. The resulting instrument contains 33 items that purport to measure nine latent factors. Aiman-Smith et al. (2005) reported that internal consistency reliabilities for all of these factors were above  $\alpha = .70$ .

Respondents indicated their agreement to the 33 survey items using a 5-point Likert-type scale, with responses ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). They responded to these items in reference to their work group. Table 1 presents the theoretical dimensions of the ICCS.

Table 1

## Theoretical Dimensions of the Innovation-Capacity Climate Survey (ICCS)

Dimension	Description
Meaningful Work	Work is meaningful, impacting customers and others in the organization.
Risk Taking	Diversity of thought, innovation, and adaptability are encouraged.
Customer Orientation	Efforts emphasize customers' needs.
Agile Decision Making	Decision making is agile, shared, and distributed.
Business Intelligence	Competitors and markets are monitored.
Open Communication	Employees are encouraged to challenge the status quo.
Empowerment	Employees experience a high degree of autonomy and independence.
Business Planning	Value chain, simulation, scenario, and risk evaluation techniques are used in business planning.
Learning Organization	Customer and employee learning experiences are incorporated into work.

Based on Aiman-Smith, Goodrich, Roberts, and Scinta (2005).

Because the ICCS is a relatively new measure of climate for innovation, some evidence for its conceptual validity as a research instrument is presented in Appendix B in the form of a comparison of its theoretical dimensions to those of other climate and culture measures found in the innovation literature. I compared the ICCS model to the four climate for innovation models reviewed by Mathisen and Einarsen (2004). Like those models, the ICCS model provides information about environments that promote creativity or innovation. The ICCS reflects the idea of support for innovation, ownership of ideas, open exchange of ideas, and challenge. It does not explicitly address commitment, trust, or shared goals. In addition, the ICCS adds new dimensions to the discussion of climate for innovation by including dimensions related to the use of business planning tools and the gathering of business intelligence. These ICCS factors reflect the collaboration between business school and industry researchers that contributed to its development.

Although none of the dimensions of the ICCS completely overlap dimensions from other instruments, the spirit of each dimension is represented to some degree in many others. Because there is some conceptual

overlap among the four instruments reviewed by Mathisen and Einarsen (2004) and the ICCS, the latter is supported as a predictor of innovation, creativity, and other outcomes such as commitment and innovative work behaviors. Given the unique business planning and business intelligence dimensions contained in the ICCS, this instrument likely assesses important information that cannot be gained using other instruments. Overall, more similarities than differences appear in the scope of content covered by the ICCS scales and other instruments that intend to assess climate for innovation; the ICCS's inclusion of factors that assess business planning and intelligence expands the domain.

**Commitment.** Commitment is conceptualized according to Meyer and Herscovitch's (2001) three-component model of commitment to the organization. These authors provided sample items to guide the creation of measures of affective, normative, and continuance (ANC) commitment. These sample items were adapted for two targets, the organization and innovation, for administration to the target sample ( $n = 383$ ). The adapted commitment instrument contained 18 items designed to measure six factors. The first three scales measure Affective, Normative, and Continuance Commitment to the Organization (ANC-O). The second three scales measure the Affective, Normative and Continuance Commitment to Innovation (ANC-I). Specifically, these six scales measure:

- (a) affective commitment to the organization (A-O);
- (b) normative commitment to the organization (N-O);
- (c) continuance commitment to the organization (C-O);
- (d) affective commitment to innovation (A-I);
- (e) normative commitment to innovation (N-I); and
- (f) continuance commitment to innovation (C-I).

All items were scored on a five-point Likert-type scale that ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). Using an adaptation of the original scales to assess ANC commitment to an organizational change initiative, Herscovitch and Meyer (2002) found that three factors accounted for 67.5% of the variance in the sample, with standardized factor loadings ranging from  $\lambda = .58$  to  $.93$ . They reported acceptable coefficient

alpha reliability coefficients for affective ( $\alpha = .94$ ), normative ( $\alpha = .86$ ) and continuance ( $\alpha = .94$ ) commitment to the change scales.

**Innovative Work Behavior.** Innovative work behavior was assessed by an adaptation of the Innovative Work Behavior (IWB) scale developed by Dorenbosch, van Engen, and Verhagen (2005). Their original instrument contained 25 items intended to measure four distinct factors: a) problem recognition, b) idea generation, c) idea promotion, and d) idea realization. These factors were hypothesized to occur across six work domains: (a) collaboration, (b) use of computer technology, (c) quality of service, (d) quality of labor, (e) work processes, and (f) use of financial resources. Although this research team found a six-factor solution fit their dataset, they could only interpret four factors. The first factor included 10 items representing idea generation and creativity behaviors. The second factor included six items representing idea realization or implementation behaviors. The third (three items) and fourth (two items) factors represented innovative behaviors toward financial resources and computer technology, respectively, but were dropped from subsequent analyses because the frequency of these behaviors was quite low for most respondents in the sample. The final factor structure was a two-factor solution indicating creativity and implementation behaviors.

Dorenbosch, van Engen, and Verhagen (2005) reported high coefficient alpha reliability estimates for the Creativity ( $\alpha = .90$ ) and Implementation ( $\alpha = .88$ ) IWB scales as well as acceptably high factor loadings (all  $\lambda > .40$ ). Although the Creativity and Implementation IWB scales should be conceptually distinct, they were found to correlate at  $r = .67$ . For these reasons, the researchers analyzed their data separately by each scale and then combined the scales to create an overall Innovative Work Behavior scale.

The final IWB instrument used in the present study is an adaptation of the IWB scales. It contains six IWB items; three to measure creative innovative work behavior (IWB-C), and three to measure implementation innovative work behavior (IWB-I). Items were selected from the original IWB scales based on the applicability of their wording to the company in which they were administered. This instrument is similar in size and content to other measures of innovative behavior (e.g., Scott & Bruce, 1994).

**Demographic Items.** The demographic items I selected for use in this study includes company membership, functional unit membership, organizational level, and organizational tenure. Although the variable



levels differed from sample to sample, intra-category consistency permitted grouping the data according the categories presented in Table 2 for most samples. One major exception is Company A, for which no functional unit information is available.

Table 2

Demographic Variables and Levels for Companies A, B, C, and D

Variable	Levels	Level Descriptions
Company	4	Company A, Company B, Company C, and Company D
Function	11	Accounting/Legal, Corporate, Customer Service, Human Resources, Environment/Health/Safety, Information Technology, Procurement, Manufacturing/Operations, Marketing/Sales, Research/Development, Quality
Level	3	Executive Manager, Manager, Non-managerial Employee
Tenure	6	Less than one yr, 1 – 5 yrs, 6 – 10 yrs, 11 – 15 yrs, 16 or more yrs

Note. Demographic information in accordance with these variables and levels is available for all companies except Company A, for which no functional unit information is available.

### Research Design

Six major methodological techniques were employed in this study. I describe the rationale for conducting each type of analysis in the subsections that follow. The six methods include:

1. Confirmatory Factor Analysis (CFA);
2. Outlier Analysis;
3. Latent Profile Analysis (LPA);
4. Multivariate Analysis of Variance (MANOVA);
5. Multivariate Analysis of Covariance (MANCOVA); and
6. Homogeneity of Variance Tests.

**Stage 1: Confirmatory Factor Analysis (CFA).** To prepare the data for subsequent analyses and to supplement the extant research on the quality of measurement of ICCS, ANC-O, ANC-I, IWB-C and IWB-I, measurement models were fitted to the data and factor scores were calculated for each latent factor using standard CFA techniques.

For the ICCS, I used the entire dataset ( $N = 1891$ ) for the CFA analyses. I randomly split the dataset into two samples, stratified by company, to ensure that half of the respondents from each company were represented in the fitting and confirming of the measurement model. I used the first split of the dataset to fit and modify the measurement model, and the second split of the dataset to confirm the measurement model. For the IWB and commitment scales, data were available only for the target sample ( $N = 383$ ) so I did not split the dataset, but instead fitted measurement models using CFA on a single sample.

CFA is an iterative process. I considered making adjustments to the measurement models for each scale in order to achieve adequate fit. Because each of the standard indices of fit is imperfect in some way, I used multiple indicators of fit (Bentler, 1990; Byrne, 1998; Reise, Widaman, & Pugh, 1993). The  $\chi^2$  ratio, Normed Fit Index (NFI), Non-normed Fit Index (NNFI), Comparative Fit Index (CFI), Root Mean Square Residual (RMR), and Root Mean Square Error Approximation (RMSEA) statistics were considered. The  $\chi^2$  ratio, which is often used to determine the basic parameters of an instrument (factor loadings, intercorrelations and unique variances), is strongly influenced by sample size (Bentler, 1990; Reise, et al., 1993). The NFI, NNFI and CFI each begin with a baseline model in which all items are presumed to be uncorrelated; incremental comparisons are then made until the hypothesized fitted model is reached. This uncorrelated model is indicated by the test for independence model  $\chi^2$  ratio; comparing the ratio for the hypothesized model to the ratio for the independence model indicates the improvement in fit, especially when large samples are used (Bentler, 1990; Byrne, 1998; Reise, et al., 1993).

GFI values can range from 0.00 to 1.00, with 1.00 indicating a perfect fit. It is customary to consider GFI statistics greater than 0.90 as indication of an acceptable fit (Byrne, 1998; Reise, et al., 1993). The RMR and RMSEA provide indications of the relationship between the fitted factor pattern of a scale and the observed factor pattern derived from the data. These statistics are equal to 0.00 when the model provides a perfect fit to the data; values less than 0.05 are generally considered indication of a good fit; and values between 0.05 and 0.08 (or sometimes 0.10) are considered a moderate fit (Byrne, 1998; Reise, et al., 1993). Item loadings and modification indices are also used to identify sources of inadequate fit, including cross-loading items and correlated factors.

When I identified inadequate fit for a measurement model, three courses of action seemed reasonable. Because cross-loading or zero-loading items can be eliminated, I first considered doing so. When item elimination was not possible or would not fix the problem, I considered collapsing scales and eliminating scales from further analyses. For example, in the presence of theoretical justification, moderately to highly correlated factors can be collapsed. In the absence of theoretical justification for collapsing highly correlated factors, one or both factors can be eliminated.

For all instruments used in the current study, the maximal reliability of each first-order factor in the final measurement model was estimated with the  $R_{MAX}$  statistic (Drewes, 2000) and internal consistency of each latent factor was assessed by coefficient alpha. Factors that failed to achieve acceptable reliability ( $R_{MAX} > .70$ , or  $\alpha > .70$ ) were excluded from further analyses.

**Stage 2: Outlier Analysis.** I conducted outlier analyses to prepare the data for LPA. The distribution of multivariate outliers can occur in several ways. First, outliers may represent small latent classes, which would be indicated by the identification of a large proportion of latent class members as multivariate outliers. Alternately, outliers may be distributed proportionately across latent classes and would therefore have little impact on the latent class solution. A third possibility is that outliers may be distributed disproportionately across latent classes, indicating that outliers do not represent small latent classes but do influence the LPA solution. In the latter case, outliers should be removed from the dataset and the LPA repeated in their absence.

I relied on Mahalanobis Distance ( $D_M$ ) and the Leverage Statistic ( $L$ ) to identify outliers on the ICCS latent factor scores. Subsequently, I conducted LPA on two sets of data. In the first analysis, the entire dataset was used except that all cases identified as multivariate outliers on the ICCS factor scores were removed (this is consistent with common practice on the treatment of multivariate outlier data). I present the results of the LPA without outliers in the Results section of this paper. In the second analysis, the LPA procedures were conducted on the entire dataset including cases identified as multivariate outliers. For these LPA solutions, the distribution of multivariate outliers across class solutions was examined post hoc to determine whether outlier removal was appropriate or necessary. I present the results of the LPA included outliers, and subsequent analysis of the distribution of multivariate outliers across latent classes, in Appendix C.

**Stage 3: Latent Profile Analysis (LPA).** I used LPA techniques to identify latent classes of individuals sharing a perception of the climate for innovation (Research Question 1) and the contribution of demographic covariates to that classification (Research Question 2). LPA is a viable way to identify groups of individuals who share a perception of climate within and across organizational boundaries. Although it is common practice to use measures of agreement to justify aggregation, as previously stated, the presence of sufficient agreement to justify aggregation indicates only whether a particular grouping schema is acceptable, not whether it is the best. LPA offers an empirical method to identify groups of people who report homogeneous perceptions of the climate for innovation. The use of LPA does not contraindicate the need for agreement measures when the goal is aggregation of individual responses to higher levels in the organization. Rather, LPA methods identify groups of people who agree without consideration of objective group membership status. In short, individuals in the same class in these analyses are grouped together because they agree.

LPA is a mixed cluster analysis technique designed to detect previously unobserved heterogeneity in a population (Nylund, Asparouhov, & Muthén, 2007). LPA offers many advantages over traditional clustering or profiling techniques, such as *k*-means clustering or Ward's method, particularly in the form of its assumptions. LPA can be used with categorical, ordinal, and continuous variables, and with combinations of these variable types. LPA does not assume linearity, normal distribution of data, or homogeneity of variances (Magdison & Vermunt, 2002). LPA is a flexible procedure that can easily incorporate covariates such as demographic variables into the profile solution and estimate the contribution of covariates to the solution. Using this analytical technique, I hoped to learn which demographic groupings (entered as covariates) are important, and how much each covariate contributes to the resultant group of climate profiles.

LPA is a variation of latent class analysis (LCA). Magdison and Vermunt (2002) directly compared the performance of LCA to *k*-means clustering technique using a simulated dataset that was designed to be favorable to the *k*-means approach. They found that LCA significantly outperformed *k*-means and, in addition, that the LCA results were almost indistinguishable from discriminant analysis of the data, for which class memberships were known.

LPA and LCA differ primarily in that LPA data include continuous variables. Using LPA, researchers assume that variability is attributable to latent class membership. Thus people who share a perception of climate represent a latent class of individuals who share a latent profile. Traditional LPA requires latent scores to be uncorrelated within class. A variation of this technique is mixture modeling with continuous variables that correlate within class (Muthén & Muthén, 1998–2007). Because the latent factor scores on the ICCS were hypothesized to be correlated, I used that technique for the LPA on the ICCS factor scores. Factor correlations were constrained to be equal across class. For each of the aforementioned covariates—company membership, functional unit membership, organizational level, and tenure—I assessed the relative contribution to the development of shared perceptions of climate (i.e., latent class membership).

**Stage 4: Multivariate Analysis of Variance (MANOVA).** I used MANOVA techniques to establish the contribution of situational and individual differences (Research Question 3 and Research Question 4, respectively). In this analysis, I predicted the latent ICCS factor scores from the demographic variables. The situational effects of the model were the main effect for company and the two-way interactions of company with functional unit, organizational level, and organizational tenure. The individual difference effects of the model were the main effects for functional unit, organizational level, and organizational tenure. I compared all MANOVA effects to assess the relative contributions of situational and individual difference contributions (Research Question 5).

**Stage 5: Multivariate Analysis of Covariance (MANCOVA).** To test the utility of latent class identification for the prediction of important organizational outcomes, I used MANCOVA techniques. This stage of analysis was conducted on the target sample only ( $N = 383$ ). I specified that the MANCOVA use latent class membership with ICCS scores entered as covariates to predict: (a) A-O, N-O, and C-O (Research Question 6); (b) A-I, N-I, and C-I (Research Question 7); and (c) IWB-C and IWB-I (Research Question 8). I conducted this analysis to answer the overall question of whether latent class membership contributes to the prediction of organizational outcomes beyond the scores that were used to identify the latent classes. In short, I wanted to find out if latent class membership improves the prediction of commitment and IWB outcomes.

I examined the multivariate tests results for evidence of overall model significance (i.e., evidence of significant prediction of all outcomes from latent class membership and ICCS covariates). For significant main effects, I examined the univariate Analyses of Variance (ANOVAs) to understand the relationships more precisely. In sum, I conducted the MANCOVAs to determine: (a) whether the latent factors of the ICCS predicted important organizational and innovation criteria, and (b) whether latent class membership contributed to these predictions. I conducted subsequent ANOVAs to identify specific predictor-outcome relationships.

**Stage 6: Homogeneity of Variance Tests.** The research hypotheses stated that as tenure increases, the variability of perceptions of innovation climate would decrease for company groups (Research Hypothesis 1) and for companies as a whole (Research Question 2). I conducted tests of the homogeneity hypothesis at multiple levels of analysis: the individual level within company, the group/functional group level within company, and last at the company level. I conducted the homogeneity of variance tests on the entire dataset for every case that had complete data on all relevant variables (e.g., tenure and functional unit, if applicable).

At the individual level within company, I specified MANOVAs to predict ICCS climate factor scores from tenure (categorical). I used these results to calculate Levene's Test for the Equality of Error Variances. Levene's Test compares residuals associated with prediction of dependent variables, to test the null hypothesis that error variances are equal across groups. At the functional group level within company, and at the company level, I conducted correlational analyses to compare the average tenure to the variances of ICCS factor scores. This method was adapted from another investigation of the homogeneity hypothesis (Denton, 1999). Negative correlations between average tenure and factor score variance would indicate that as tenure increases, variability of climate perceptions decrease. Although the original homogeneity hypothesis was made at the company level, due to the small number of company samples ( $N = 5$ ), this analysis was also conducted at the functional group level within each company.

## Results

### Confirmatory Factor Analysis (CFA)

**Predictor Scales.** I conducted a CFA to test and confirm the measurement model of the ICCS instrument using Mplus software (Muthén & Muthén, 2007). I randomly split the entire dataset ( $N = 1891$ ) into two samples, stratified by company to ensure that half of the respondents from each company were represented in the fitting and confirming of the measurement model. The result of this split by company membership is presented in Table 3. To confirm that random assignment resulted in the distribution of other demographic variables of interest approximately equally across the two splits of the data, I calculated and reviewed frequency data for each demographic variable. Frequency data for functional unit membership, organizational level, and organizational tenure for each of the two splits of the data are presented in Tables 4 – 6, respectively. I found that the demographic representation across the two splits of the data was approximately equal.

The first split of the dataset ( $n = 945$ ) was intended for use in fitting the model and for modifying it, as required. I specified the theoretical and measurement model for the ICCS, as depicted in Figure 1. This model is a nine-factor correlated model. All factor intercorrelations, factor loadings, and error terms were estimated. To generate a standardized solution, the variances for the nine latent factors were set equal to 1.00.

Table 3

Frequency Data for Company Membership for Two Random Splits of Complete Dataset

Level	Split 1 ( $n = 945$ )		Split 2 ( $n = 946$ )	
	<i>f</i>	%	<i>f</i>	%
Company A	203	21.5	203	21.5
Company B	246	26.0	245	25.9
Company C	151	16.0	152	16.1
Company D – Time 1	154	16.3	154	16.3
Company D – Time 2 (Target Sample)	191	20.2	192	20.3

Note.  $N = 1891$ .

Table 4

Frequency Data for Functional Unit Membership for Two Random Splits of Complete Dataset

Functional Unit	Split 1		Split 2	
	<i>f</i>	%	<i>f</i>	%
Business and General Management / Corporate	25	2.6	32	3.4
Supply Chain (Procurement, Customer Service, Operations Planning)	42	4.4	45	4.8
Manufacturing and Operations	252	26.7	274	29.0
Environmental Health and Safety	21	2.2	14	1.5
Human Resources	32	3.4	27	2.9
Marketing and Sales	161	17.0	130	13.7
Research and Development	95	10.1	90	9.5
Information Technology	26	2.8	34	3.6
Finance/Accounting/Legal	67	7.1	67	7.1
Competitive Intelligence	9	1.0	10	1.1
Missing	215	22.8	223	23.6

Note. For Split 1,  $n = 945$ ; for Split 2,  $n = 946$ .

Table 5

Frequency Data for Organizational level for Two Random Splits of Complete Dataset

Organizational Level	Split 1		Split 2	
	<i>f</i>	%	<i>f</i>	%
Non-manager	477	51.1	474	50.7
Manager	377	40.4	456	48.9
Executive	79	8.5	92	9.8
Missing	12	1.3	11	1.2

Note. For Split 1,  $n = 945$ ; for Split 2,  $n = 946$ .



Table 6

Frequency Data for Organizational Tenure for Two Random Splits of Complete Dataset

Organizational Tenure	Split 1 ( <i>n</i> = 945)		Split 2 ( <i>n</i> = 946)	
	<i>f</i>	%	<i>f</i>	%
Less than 1 Year	51	5.4	51	5.4
1 – 5 Years	258	27.3	243	25.7
6 – 10 Years	142	15.0	147	15.5
11 – 15 Years	129	13.7	125	13.2
16 or More Years	346	36.6	357	37.7
Missing	19	2.0	23	2.4

Note. For Split 1, *n* = 945; for Split 2, *n* = 946.

For the hypothesized ICCS model on the first split of the data,  $\chi^2(459) = 1949.43$ ,  $p < .0001$ , suggesting a poor fit. However, the sample size was large and other indicators of fit were more supportive, approaching or exceeding minimal criteria for acceptable fit (GFI = .88, CFI = .91, NNFI = .89, NFI = .88). The RMR and RMSEA statistics for the hypothesized model were .057 and .057, respectively, indicating a moderate fit to the data. Based on the fit statistics I concluded that the hypothesized nine-factor model provided an adequate fit to the first split of the ICCS data. Although model fit could have been improved, no theoretical rationale was found to justify doing so and attempts to improve model fit could have overfit the model to the first split of the data.

I specified the same hypothesized measurement model of the ICCS to my second split of the dataset (*n* = 946) in an attempt to confirm the fit on an independent sample. For the second split,  $\chi^2(459) = 1867.38$ ,  $p < .0001$ . As I found for the first split of the data, the other fit statistics generated, approached, or exceeded generally accepted levels (GFI = .89, CFI = .92, NNFI = .90, NFI = .89, RMR = .056, RMSEA = .57). Based on the fit statistics generated, I concluded that the model represented an adequate fit to both splits of the data. The CFA fit statistics generated for both splits are presented in Table 7.

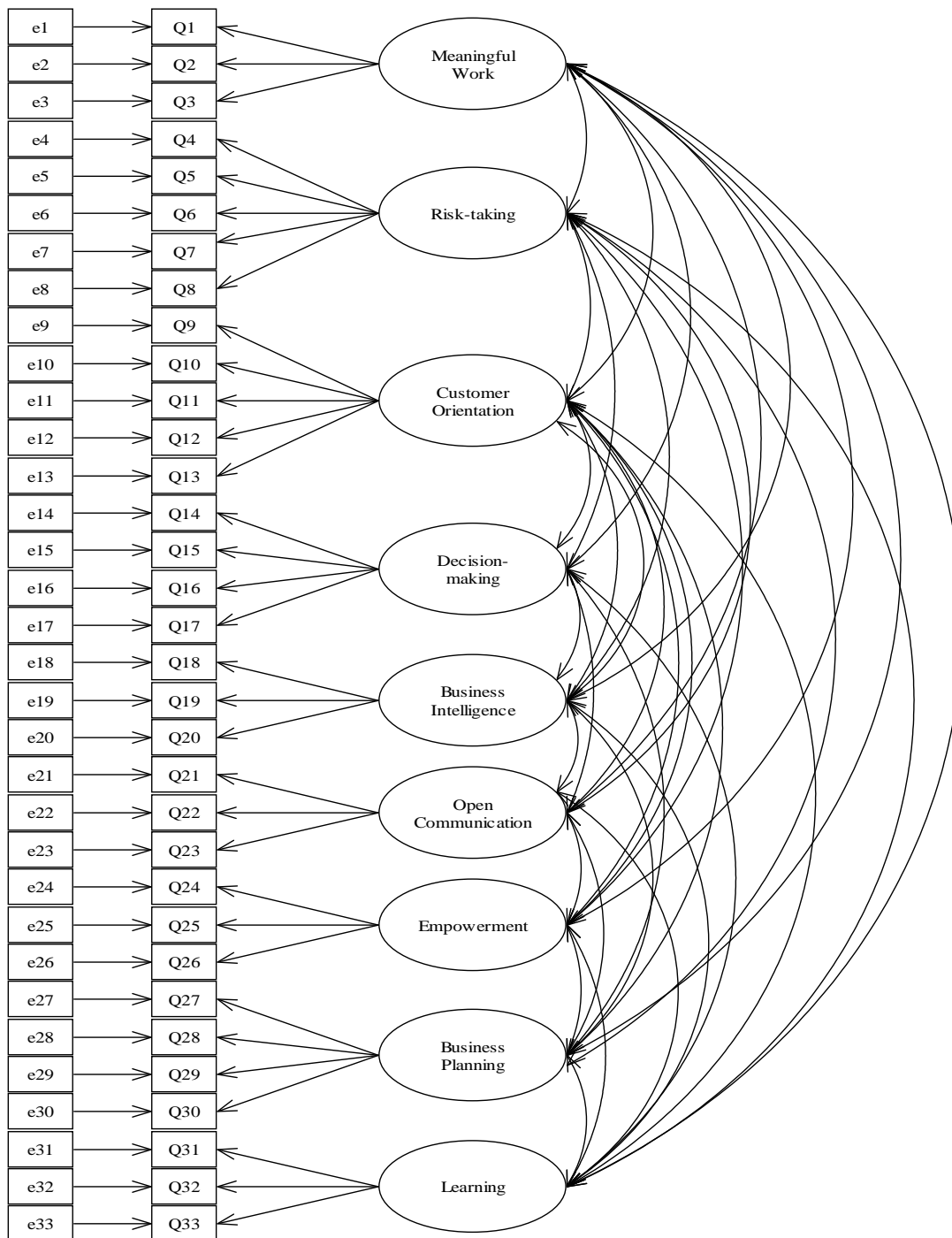


Figure 1. Measurement Model for Innovation-Capacity Climate Survey (ICCS)

Table 7

## Fit Statistics for Innovation-Capacity Climate Survey (ICCS)

Fit Statistic	Split 1	Split 2
Goodness of Fit Index (GFI)	0.8823	0.8884
Root Mean Square Residual (RMR)	0.0568	0.0562
Root Mean Square Error of Approximation (RMSEA)	0.0568	0.0570
Bentler's Comparative Fit Index (CFI)	0.9073	0.9155
Bentler and Bonnet's Non-Normed Fit Index (NNFI)	0.8934	0.9029
Bentler and Bonnet's NFI	0.8826	0.8915

Note. For Split 1,  $n = 945$ ; for Split 2,  $n = 946$ .

I examined the standardized factor loadings and factor correlations to identify sources of inadequate fit. Item loadings for both splits of the data are presented in Table 8. For the first split, standardized factor loadings ranged from  $\lambda = .55$  to  $\lambda = .89$ . For the second split, standardized factor loadings ranged from  $\lambda = .52$  to  $\lambda = .87$ . For both splits, all standardized factor loadings were modest to high and statistically significant ( $p < .001$ ), suggesting adequate model fit. I correlated the standardized item loadings for the first and second splits to determine the degree to which they were similar. The correlation was found to be  $r = .93$ ,  $p < .001$ , indicating a very similar pattern of correlations between the two samples.

I also analyzed the factor intercorrelations for both splits of the data to assess model fit. The factor intercorrelations among the factors on the ICCS for both data subsets are presented in Table 9. For the first split, factor intercorrelations ranged from  $r = .29$  to  $r = .82$ . For the second split, factor correlations ranged from  $r = .29$  to  $r = .80$ . All factor intercorrelations were statistically significant at the  $p < .0001$  level. The factor intercorrelations for both sets of data were modest to high, with the average correlation  $r = .51$ . Higher correlations for both samples were found between factors that were expected to correlate (e.g., Empowerment and Open Communication), and lower correlations were found for both samples between factors not expected to be highly correlated (e.g., Meaningful Work and Business Intelligence).

Table 8

Standardized Estimates of Manifest Variable Equations for Innovation-Capacity Climate Survey by Split

Factor	Item	Split 1		Split 2	
		Loading	Error	Loading	Error
Meaningful Work	1	0.753	0.658	0.775	0.632
Meaningful Work	2	0.654	0.757	0.650	0.760
Meaningful Work	3	0.652	0.758	0.713	0.701
Risk Taking	4	0.773	0.634	0.764	0.645
Risk Taking	5	0.835	0.551	0.814	0.581
Risk Taking	6	0.726	0.688	0.700	0.714
Risk Taking	7	0.694	0.720	0.705	0.710
Risk Taking	8	0.753	0.658	0.720	0.694
Customer Orientation	9	0.750	0.662	0.750	0.661
Customer Orientation	10	0.672	0.741	0.727	0.687
Customer Orientation	11	0.835	0.551	0.827	0.562
Customer Orientation	12	0.815	0.579	0.829	0.559
Customer Orientation	13	0.835	0.550	0.855	0.519
Agile Decision Making	14	0.653	0.757	0.708	0.707
Agile Decision Making	15	0.693	0.721	0.735	0.679
Agile Decision Making	16	0.610	0.792	0.681	0.733
Agile Decision Making	17	0.660	0.751	0.637	0.771
Business Intelligence	18	0.744	0.668	0.751	0.660
Business Intelligence	19	0.684	0.729	0.720	0.694
Business Intelligence	20	0.644	0.765	0.676	0.737
Open Communication	21	0.856	0.517	0.866	0.500
Open Communication	22	0.838	0.546	0.843	0.539
Open Communication	23	0.748	0.663	0.780	0.626

Table 8 Continued

Empowerment	24	0.822	0.570	0.850	0.527
Empowerment	25	0.787	0.617	0.828	0.562
Empowerment	26	0.712	0.720	0.710	0.704
Business Planning	27	0.802	0.598	0.785	0.620
Business Planning	28	0.788	0.616	0.755	0.656
Business Planning	29	0.689	0.724	0.675	0.738
Business Planning	30	0.585	0.811	0.656	0.755
Learning Organization	31	0.553	0.833	0.517	0.856
Learning Organization	32	0.868	0.496	0.858	0.514
Learning Organization	33	0.854	0.520	0.844	0.536

Note. For Split 1,  $n = 945$ . For Split 2,  $n = 946$ . All factor loadings are statistically significant at the  $p < .001$  level.

I calculated the bivariate correlation between the latent factor correlations obtained for the first split and second split to estimate the degree to which the factor correlations were similar. The correlation between factor correlations of the first split and second split was  $r = .94$ ,  $p < .001$ , indicating a strong relationship between the factor intercorrelations between the two splits on the ICCS scales.

The final analysis of the split ICCS data involved the evaluation of  $R_{MAX}$  maximal reliability and Coefficient Alpha internal consistency reliability statistics. Table 10 presents the  $R_{MAX}$  and Coefficient Alpha statistics for each ICCS scale.  $R_{MAX}$  and Coefficient Alpha reliability estimates above  $r = .70$  are considered acceptable for use in research; and values exceeding  $r = .80$  are considered acceptable for use in practice (Nunnally, 1970). For both splits of the data, maximal reliability statistics were found to be high enough ( $R_{MAX} = .75$  to  $.91$ ) for research use. Internal consistency estimates for both splits were also found to be acceptably high for use in research ( $\alpha = .72$  to  $.90$ ).

Table 9

Factor Intercorrelations for Innovation-Capacity Climate Survey (ICCS) for First and Second Splits

Latent Factor	F1	F2	F3	F4	F5	F6	F7	F8	F9
First Split									
F1. Meaningful Work	1.00								
F2. Risk Taking	0.64	1.00							
F3. Customer Orientation	0.55	0.63	1.00						
F4. Agile Decision Making	0.62	0.82	0.58	1.00					
F5. Business Intelligence	0.30	0.41	0.50	0.45	1.00				
F6. Open Communication	0.54	0.74	0.46	0.72	0.32	1.00			
F7. Empowerment	0.57	0.66	0.46	0.67	0.31	0.80	1.00		
F8. Business Planning	0.29	0.45	0.46	0.54	0.50	0.38	0.35	1.00	
F9. Learning Organization	0.38	0.48	0.62	0.49	0.52	0.37	0.38	0.51	1.00
Second Split									
Latent Factor	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1. Meaningful Work	1.00								
F2. Risk Taking	0.59	1.00							
F3. Customer Orientation	0.56	0.60	1.00						
F4. Agile Decision Making	0.62	0.80	0.61	1.00					
F5. Business Intelligence	0.32	0.39	0.52	0.54	1.00				
F6. Open Communication	0.51	0.75	0.43	0.71	0.29	1.00			
F7. Empowerment	0.52	0.64	0.47	0.57	0.29	0.76	1.00		
F8. Business Planning	0.36	0.48	0.49	0.58	0.65	0.38	0.37	1.00	
F9. Learning Organization	0.41	0.52	0.56	0.57	0.52	0.39	0.34	0.55	1.00

Note:  $N = 945$  for first split,  $N = 946$  for second split. All correlations significant at  $p < .0001$ .

Table 10

## Maximal Reliability and Internal Consistency Reliability for the Innovation-Capacity Climate Survey (ICCS)

Latent Factor	First Split ( $n = 945$ )		Second Split ( $n = 946$ )	
	$R_{MAX}$	$\alpha$	$R_{MAX}$	$\alpha$
Meaningful Work	0.75	0.72	0.78	0.75
Risk Taking	0.89	0.87	0.87	0.86
Customer Orientation	0.90	0.89	0.91	0.90
Agile Decision Making	0.75	0.75	0.79	0.78
Business Intelligence	0.75	0.73	0.78	0.76
Open Communication	0.88	0.85	0.88	0.87
Empowerment	0.84	0.81	0.87	0.82
Business Planning	0.84	0.80	0.84	0.81
Learning Organization	0.88	0.78	0.87	0.75

Note:  $R_{MAX}$  is the maximal reliability estimate,  $\alpha$  is the Coefficient Alpha internal consistency reliability estimate.

Based on all fit statistics, item loadings, factor correlations, maximal reliability, and internal consistency reliability, I concluded that the hypothesized nine-factor, correlated model provides an adequate fit to the ICCS data. Although the measurement model may have been improved, I found no measurement or theoretical rationale for doing so. I did not consult the modification indices and I made no modifications to the hypothesized ICCS model.

I combined the subsets (splits) of ICCS data to generate model estimates for the entire sample and factor scores on each ICCS scale for each participant. I repeated the CFA analysis of the hypothesized model on the combined dataset. Model fit statistics were slightly improved for the entire sample, with all fit statistics except  $\chi^2$  falling within the range of acceptability for model fit (GFI = .90, CFI = .92, NNFI = .90, NFI = .90, RMR = .055, RMSEA = .056). Factor intercorrelations for the ICCS factors calculated using the full dataset are presented in Table 11. Table 12 presents the standardized item statistics for the confirmed ICCS model on the complete dataset.

In subsequent analyses, I used first-order latent factor scores for the ICCS. First-order factor scales were calculated automatically by Mplus software by multiplying the average raw score by its standardized factor loading for each first-order factor.

Factor scores have a theoretical advantage over simple composite scores. Composite scores suggest that the aggregate variable is a construction—that it is constructed by the addition or averaging of items. Composite variables are therefore linked to the items from which they are constructed. Latent factors, however, are not bound to items in this way. Factor scores suggest that the latent factor affects ratings on particular items and do not imply that the items are the only indicators of a factor.

Table 11

Factor Intercorrelations for Innovation-Capacity Climate Survey (ICCS)

Latent Factor	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1. Meaningful Work	1.00								
F2. Risk Taking	0.62	1.00							
F3. Customer Orientation	0.55	0.61	1.00						
F4. Agile Decision Making	0.62	0.81	0.59	1.00					
F5. Business Intelligence	0.31	0.40	0.51	0.49	1.00				
F6. Open Communication	0.52	0.75	0.44	0.71	0.30	1.00			
F7. Empowerment	0.54	0.65	0.46	0.62	0.30	0.78	1.00		
F8. Business Planning	0.33	0.47	0.48	0.59	0.58	0.38	0.36	1.00	
F9. Learning Organization	0.39	0.50	0.59	0.53	0.52	0.38	0.36	0.53	1.00

Note.  $N = 1891$ . \*All correlations significant at  $p < .0001$ .



Table 12

Standardized Factor Loadings, Error, and  $R^2$  values for Innovation-Capacity Climate Survey (ICCS)

Factor	Item	Loading	Error	$R^2$
Meaningful Work	1	0.736	0.646	0.582
Meaningful Work	2	0.653	0.757	0.427
Meaningful Work	3	0.683	0.731	0.466
Risk Taking	4	0.769	0.639	0.592
Risk Taking	5	0.824	0.566	0.680
Risk Taking	6	0.713	0.701	0.508
Risk Taking	7	0.699	0.715	0.488
Risk Taking	8	0.737	0.678	0.543
Customer Orientation	9	0.750	0.661	0.563
Customer Orientation	10	0.700	0.715	0.489
Customer Orientation	11	0.831	0.557	0.690
Customer Orientation	12	0.822	0.557	0.676
Customer Orientation	13	0.845	0.0535	0.714
Agile Decision Making	14	0.681	0.733	0.463
Agile Decision Making	15	0.715	0.699	0.511
Agile Decision Making	16	0.647	0.762	0.419
Agile Decision Making	17	0.648	0.762	0.420
Business Intelligence	18	0.751	0.661	0.564
Business Intelligence	19	0.702	0.712	0.493
Business Intelligence	20	0.659	0.753	0.434
Open Communication	21	0.861	0.508	0.742
Open Communication	22	0.841	0.541	0.708
Open Communication	23	0.764	0.645	0.584
Empowerment	24	0.836	0.549	0.699
Empowerment	25	0.808	0.589	0.653

Table 12 Continued

Empowerment	26	0.711	0.703	0.506
Business Planning	27	0.793	0.609	0.630
Business Planning	28	0.772	0.636	0.596
Business Planning	29	0.683	0.731	0.466
Business Planning	30	0.620	0.785	0.384
Learning Organization	31	0.534	0.845	0.285
Learning Organization	32	0.863	0.505	0.745
Learning Organization	33	0.850	0.528	0.722

Note.  $N = 1891$ . Loading is the standardized factor loading; error is the standardized estimate of error. All factor loadings are statistically significant at the  $p < .001$  level.

**Outcome Scales.** The hypothesized three-factor model for ANC-O, three-factor model for ANC-I, and two-factor IWB were also tested using CFA techniques. The hypothesized models are presented in Figures 2 – 4, respectively. The ANC-O and ANC-I measurement models are independent three-factor correlated models, with three indicator items per factor. The IWB measurement model is a two-factor correlated model with three indicator items per factor. Modeling was conducted independently for ANC-O, ANC-I, and IWB. For these three models, all factor intercorrelations, factor loadings, and error terms were estimated. To generate a standardized solution, the variances for the latent factors were set equal to 1.00.

For the ANC-O, ANC-I and IWB scales, data were only available for the target sample ( $N = 383$ ). Because of the smaller sample size, I did not split this sample but instead conducted the analyses on the full target sample. For ANC-O,  $\chi^2(24) = 122.83$ ,  $p < .0001$ . For ANC-I,  $\chi^2(24) = 84.67$ ,  $p < .0001$ . For IWB,  $\chi^2(8) = 9.03$ ,  $p = .3398$ . The additional fit statistics generated for these models are presented in Table 13.

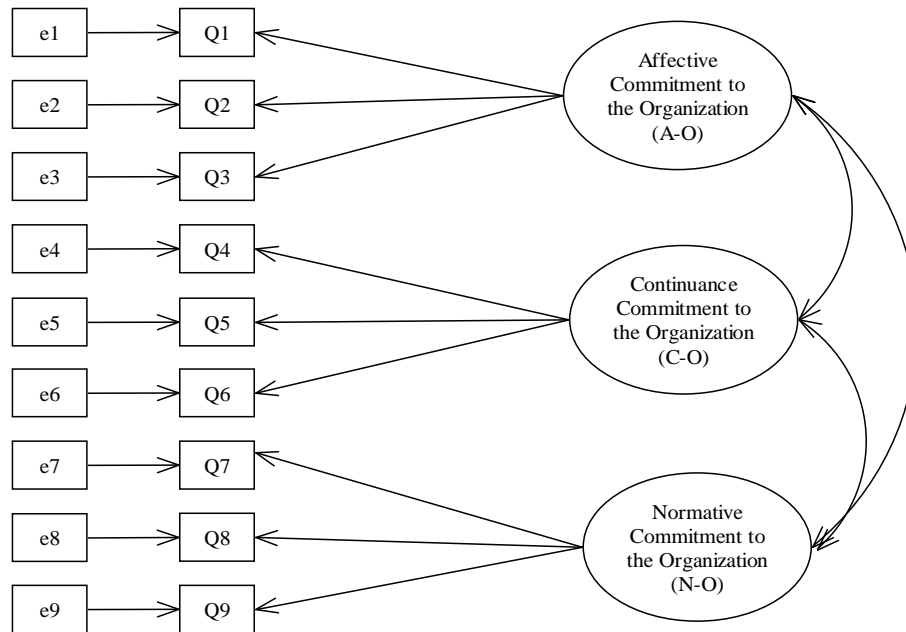


Figure 2. Measurement Model for Affective, Normative, and Continuance Commitment to Organization

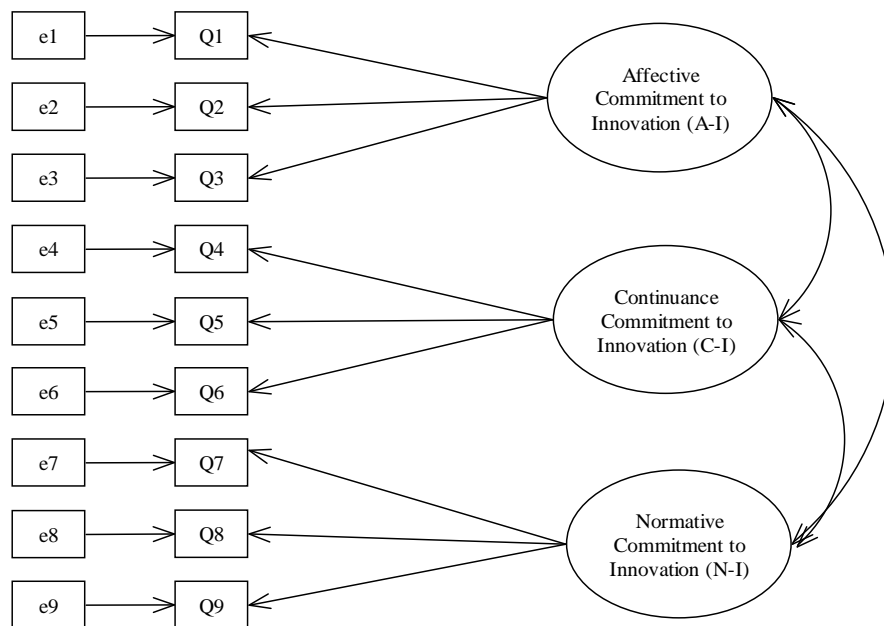


Figure 3. Measurement Model for Affective, Normative, and Continuance Commitment to Innovation

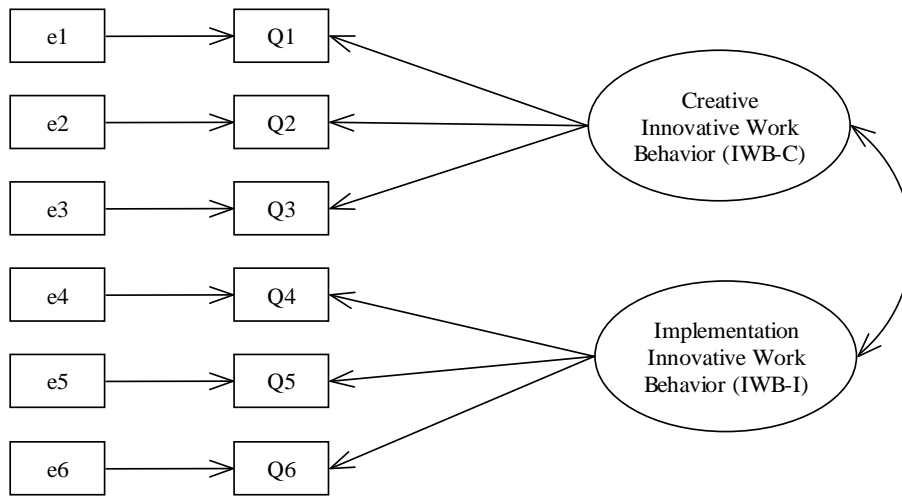


Figure 4. Measurement Model for Innovative Work Behavior

Table 13

Confirmatory Factor Analysis (CFA) Fit Statistics for Outcome Scales

Fit Statistic	ACN-O	ACN-I	IWB
Goodness of Fit Index (GFI)	.9368	.9507	.9915
Root Mean Square Residual (RMR)	.0838	.0339	.0093
Root Mean Square Error of Approximation (RMSEA)	.1077	.0836	.0191
Bentler's Comparative Fit Index (CFI)	.9160	.9454	.9990
Bentler and Bonnet's Non-normed Fit Index (NNFI)	.8741	.9181	.9981
Bentler and Bonnet's NFI	.8987	.9262	.9912

Note. ANC-O ( $n = 356$ ) is the Affective, Normative, and Continuous Commitment to the Organization Scales; ACN-I ( $n = 363$ ) is the Affective, Normative and Continuance Commitment to Innovation Scales; and IWB ( $n = 353$ ) is the Innovative Work Behavior Scales.

The fit statistics for the IWB scales indicated an excellent fit of the hypothesized two-factor model to the data with most values approaching indication of a perfect fit. For the ANC-I, the fit statistics suggest a good fit of the model to the data (GFI = .9057, CFI = .9454, NNFI = .9181, NFI = .9262, RMR = .0339, RMSEA = .0836). For the ANC-O, the fit statistics provided mixed evidence for model fit. While the GFI and CFI provide support for model fit (.9368 and .9160, respectively), others approach the range for acceptable fit (RMR = .0838, NFI = .8987) and some fall out of range for acceptable fit (RMSEA = .1077, NNFI = .8741). Because the fit statistics for the ANC-O suggest there may be some problems with model fit, I examined additional indicators of possible model misfit.

Item statistics, including standardized factor loadings, error estimates, and  $R^2$  values for the ANC-O scales, are presented in Table 14. For most of the items on the ANC-O, factor loadings and  $R^2$  values were sufficiently high. However, item number eight on the N-O subscale, is a reverse-scored item that appeared to be problematic. It has a negative standardized factor loading ( $\lambda = -0.532$ ) and relatively low  $R^2$  value ( $R^2 = 0.283$ ). Modification indices did not indicate that model fit could be improved by loading this item on either of the other two factors. The option to eliminate this item was problematic in that doing so would have left only two indicators for the N-O latent factor. Factor elimination for the N-O factor was a viable alternative pending the examination of other results.

Item statistics, including standardized factor loadings, error estimates, and  $R^2$  values for the ANC-I scales are presented in Table 15. For the ANC-I, standardized factor loadings are all positive and all but one are moderate to high.  $R^2$  values are moderate to high for all but one item. Item six on the C-I subscale is a reverse-scored item. Although the factor loading of this item is statistically significant, it is modest.

Item statistics including standardized factor loadings, error estimates, and  $R^2$  values for the IWB scales, are presented in Table 16. Standardized factor loadings and  $R^2$  values for all items on the IWB subscales are acceptably high, suggesting good fit of the model to the data. For each of the outcome subscales, I calculated the  $R_{MAX}$  statistic to assess maximal reliability and calculated the coefficient alpha statistic to assess internal consistency reliability. These results are presented in Table 17.

Table 14

Standardized Factor Loadings, Error, and  $R^2$  for Affective, Continuance, and Normative Commitment to the Organization (ACN-O) Subscales

Item	Subscale	Loading	Error	$R^2$
1	A-O	0.908	0.419	0.824
2	A-O	0.853	0.523	0.727
3	A-O	0.754	0.657	0.569
4	C-O	0.610	0.792	0.372
5	C-O	0.612	0.791	0.375
6	C-O	0.861	0.510	0.740
7	N-O	0.736	0.677	0.542
8	N-O	-0.532	0.847	0.283
9	N-O	0.586	0.810	0.344

Note.  $N = 356$ . All factor loadings are statistically significant at the  $p < .001$  level. A-O is affective commitment, C-O is continuance commitment, and N-O is normative commitment to the organization.

Table 15

Standardized Factor Loadings, Error, and  $R^2$  for Normative Commitment to Innovation (ANC-I) Subscales

Item	Subscale	Loading	Error	$R^2$
1	A-I	0.554	0.833	0.307
2	A-I	0.681	0.732	0.464
3	A-I	0.884	0.468	0.781
4	C-I	0.816	0.578	0.666
5	C-I	0.887	0.462	0.787
6	C-I	0.252	0.968	0.064
7	N-I	0.696	0.718	0.484
8	N-I	0.857	0.515	0.735
9	N-I	0.709	0.705	0.503

Note.  $N = 356$ . All factor loadings are statistically significant at the  $p < .01$  level. A-I is affective commitment to innovation; C-I is continuance commitment to innovation; and N-I is normative commitment to innovation.

Table 16

Standardized Factor Loadings, Error, and  $R^2$  for Innovative Work Behavior (IWB) Subscales

Item	Subscale	Loading	Error	$R^2$
1	IWB-C	0.787	0.617	0.617
2	IWB-C	0.818	0.575	0.670
3	IWB-C	0.711	0.704	0.505
4	IWB-I	0.804	0.595	0.646
5	IWB-I	0.778	0.628	0.605
6	IWB-I	0.786	0.618	0.618

Note.  $N = 356$ . All factor loadings are statistically significant at the  $p < .001$  level. IWB-C is creative innovative work behavior; IWB-I is implementation innovative work behavior.

Table 17

Maximal Reliability and Internal Consistency Reliability Estimates for Outcome Scales.

Survey	Subscale	$R_{MAX}$	$\alpha$
ANC-O	A-O	0.914	0.868
ANC-O	C-O	0.753	0.745
ANC-O	N-O	0.666	-0.434
ANC-I	A-I	0.845	0.723
ANC-I	C-I	Unable to Calculate	0.638
ANC-I	N-I	0.95	0.794
IWB	IWB-C	0.84	0.813
IWB	IWB-I	0.832	0.833

Note.  $R_{MAX}$  is the maximal reliability estimate;  $\alpha$  is the Coefficient Alpha reliability estimate. ANC-O and ANC-I are affective, normative, and continuance commitment to the organization and to innovation surveys, respectively. IWB is innovative work behavior survey. A-O, C-O, and N-O are affective, continuous, and normative commitment to the organization, respectively. A-I, C-I, and N-I are affective, continuous, and normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation innovative work behaviors, respectively.

Two subscales, N-O and C-I, fail to meet the criteria for use in research or practice. For the N-O scale,  $R_{MAX} = .67$  and  $\alpha = .43$ . For the C-I subscale,  $R_{MAX}$  could not be calculated and  $\alpha = .64$ . These subscales also demonstrated problematic factor loadings and  $R^2$  values, most likely due in part to the inclusion of reverse-scored items on each. The low number of items on each scale (three) makes eliminating items problematic. Due to the maximal and internal consistency reliability problems already noted with the N-O and C-I commitment subscales, I decided to exclude these subscales from subsequent analyses. I calculated latent factor scores for each respondent in the target sample on the four commitment outcome subscales and two IWB subscales using Mplus.

The intercorrelation matrix for all outcome variables, including the two variables deleted from subsequent analyses, is presented in Table 18. The correlations among the outcomes ranged from  $r = .14$  to  $r = .71$ , with all but one correlation in the modest range (below  $r = .45$ ). The highest correlation was found between the two IWB subscales.

Table 18

Outcome Factor Intercorrelation Matrix

	A-O	C-O	N-O	A-I	C-I	N-I	IWB-C	IWB-I
A-O	1.00							
C-O	0.13*	1.00						
N-O	0.17**	0.35**	1.00					
A-I	0.16**	0.00	0.04	1.00				
C-I	-0.08	0.28**	0.12*	0.31**	1.00			
N-I	0.25**	0.11*	0.26**	0.45**	0.40**	1.00		
IWB-C	0.09	0.01	0.03	0.37**	0.12*	0.24**	1.00	
IWB-I	0.06	-0.14**	0.01	0.34**	0.09	0.24**	0.71**	1.00

Note. \*Statistically significant at  $p < .05$ ; \*\*Significant at  $p < .01$ . A-O, C-O, and N-O are affective, continuous, and normative commitment to the organization, respectively. A-I, C-I, and N-I are affective, continuous, and normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation innovative work behaviors, respectively.



### Outlier Analysis

I calculated two statistics for the ICCS latent factor scores to identify multivariate outliers, including Mahalanobis Distance ( $D_M$ ) and Leverage ( $L$ ) values. These were calculated using multivariate regression in which the average ICCS factor score was regressed on the nine ICCS latent factor scores. The critical value for the identification of outliers for  $D_M$  was  $\chi^2(9) = 27.88$ ,  $\alpha = .001$ . The critical value for ( $L$ ) was set to  $2p/n$ , where  $p$  is the number of parameters and  $n$  is the number of cases, so that  $L_{crit} = .0095$ . Twenty-two cases (1.2%) were identified as multivariate outliers using the Mahalanobis Distance criterion and 139 cases (7.4%) were identified as multivariate outliers using the Leverage value criterion. All 22 of the cases identified by  $D_M$  were also identified as multivariate outliers by the Leverage value.

I flagged all cases identified as multivariate outliers in the dataset and I conducted the LPAs described below without multivariate outlier data. I repeated the LPA with the outlier data included and this time the impact of outlier data was examined. As previously mentioned, the results of the LPA analysis with outlier data included are presented in Appendix C.

Herein, I provide a brief overview of the findings related to outliers from Appendix C. I found that the multivariate outliers were disproportionately distributed across the class solutions generated for the entire dataset, including outlier data. Furthermore, the occurrence of multivariate outliers did not suggest that these cases represented small, independent classes. Whereas this latter possible finding (or a finding of random or proportionate distribution of outliers) would have suggested that the outliers did not detrimentally affect the class solution and therefore could have been included in the LPA analyses. However, the nonrandom distribution of outliers in the absence of evidence of small independent classes suggests that the outlier data significantly affects the class solution and in a manner that cannot be explained by the data. I concluded that, although this is an interesting finding that deserves additional scrutiny, removal of the multivariate outlier data prior to LPA analysis was a prudent course of action. The results of the LPA analyses in the absence of multivariate outlier data are presented below.

**Latent Profile Analysis (LPA)**

The variation of traditional LPA used in this study is mixture modeling with continuous variables that correlate within class (Muthén & Muthén, 1998 – 2007). Because I hypothesized that the latent factor scores were correlated, I adapted this technique for the LPA on the ICCS factor scores. I performed a latent profile analysis (LPA) on the nine ICCS latent factor scores using Mplus software (Muthén & Muthén, 2007). My main goals for the LPA analysis were to identify: (a) latent classes of individuals who share a profile of ICCS factor scores, and (b) the extent to which demographic covariates (company membership, functional unit membership, organizational role, and organizational tenure) are related to the identification of latent classes. I conducted two variations of the LPA model.

The first LPA model generated is LPA Model A. LPA allows for latent class membership to be identified based on profile similarity and for estimates of the contribution of covariates to be estimated simultaneously. This is the ideal method to meet the goals for the LPA analysis. The relationships of the covariate data are estimated at the same time as, and affect the results of, the latent class solution. However, because Mplus does not allow missing covariate data, I had to remove all cases with missing demographic covariates prior to analysis. For most covariates, only a few cases were deleted. For Company A, however, no functional unit information was available and so all data for this company were deleted from consideration in Model A.

I devised LPA Model B in an effort to preserve sample size, replicate findings, produce evidence of the stability of the LPA Model A results, and explore other issues related to LPA analyses. In LPA Model B, the demographic data were not entered into the LPA analysis so the class solution was not directly influenced by the covariates. However, because company and organizational level were found to be significant predictors of the profile solution, it is likely that these covariates will affect the class solution, though not directly. In any case, this analysis does not permit simultaneous evaluation of covariate effects. Although this model identifies profiles on the ICCS, (the first goal of the analysis), it does not address the second goal. To do so, after the LPA Model B results were generated, I conducted logistic regression analyses to examine the relationships between the covariates and the latent class solution.

For both LPA Model A and LPA Model B, I used an iterative method to determine the best-fitting solution to the LPA. I began these processes with the prediction of two latent profiles, after which I subsequently increased the number of predicted latent profiles until the fit declined. Fit was indicated by Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Entropy, and the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test. The results for LPA Model A and LPA Model B are presented below. Sample summary statistics by company membership, functional unit membership, organizational level, and organizational tenure are presented in Appendix D.

**LPA Model A.** In LPA Model A, I used nine latent factor scores and four categorical covariates (company, functional unit, organizational level, and tenure) to identify latent classes of individuals who share a latent profile on the ICCS. The Mplus analysis type was specified as mixture with an integration algorithm. The ICCS latent factor scores were free to correlate with the constraint that the correlations be held constant across classes. The demographic covariance matrices were set free to differ. The theoretical model tested by LPA Model A is presented in Figure 5.

Analysis of LPA Model began with the specification of a two-class model; class size was increased in subsequent iterations until fit declined. The fit statistics generated for four iterations of LPA Model A are presented in Table 19. I did not perform any additional iterations. The AIC and BIC are theoretical indicators of model fit and are used when comparing competing non-nested models. Lower AIC and BIC values are preferable. For each iteration, the AIC value decreased. The BIC decreased for the three-class solution but rose for the four- and five-class solutions. Entropy values that approach 1.0 are considered an indication of good model fit. Although there is no cut-off value for entropy, it is used to compare model fit when all else is equal. Entropy decreased with each iteration of the model, from a high of .90 with the two-class solution.

The explicit test of model fit is the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test. It compares the model to  $k$  classes to the model with  $(k-1)$  classes. When  $p > .05$ , the model with  $k$  classes is rejected and the model with  $k-1$  classes is judged to fit. The Vuong-Lo-Mendell-Rubin Likelihood Ratio Test generated  $p = 0.000$  for the two-class model, indicating that the two-class solution is significantly better than a single-class model.

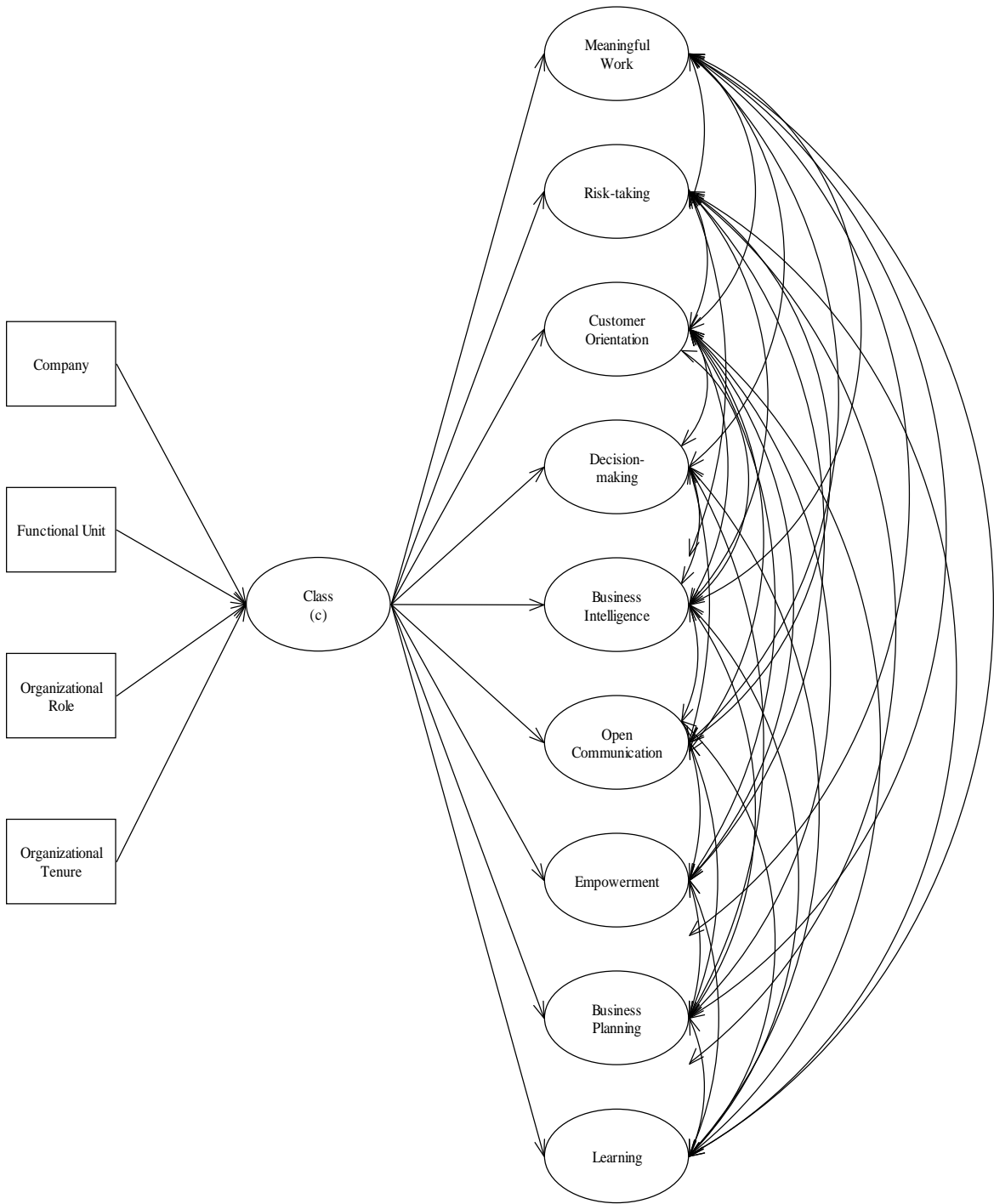


Figure 5. Theoretical Latent Profile Analysis Model A with Nine Latent Continuous Innovation-Capacity Climate Survey (ICCS) Factor Scores and Four Categorical Demographic Covariates

Table 19

Latent Profile Analysis (LPA) Model A Fit Statistics

Statistics	Number of Classes ( <i>k</i> )			
	2	3	4	5
Akaike Information Criterion (AIC)	33924.80	33738.98	33686.93	33646.84
Bayesian Information Criterion (BIC)	34365.11	34251.81	34272.28	34304.71
Entropy	0.90	0.83	0.84	0.71
Vuong-Lo-Mendell-Rubin Likelihood Ratio (for <i>k</i> versus <i>k</i> – 1 classes) <i>p</i> value	0.00	0.08	0.74	0.92

Note. *N* = 1313.

When comparing the three-class model to the two-class model, however, the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test generated a nonsignificant *p* value = .08. The fit statistics suggest that the two-class solution is the most appropriate for these data.

The overall contribution of the covariates in this model is determined by a  $\chi^2$  test that compares the specified model, in which covariates are free to differ, versus the null model in which the covariates are constrained to be constant. The test for the significance of the covariates for two-class solution resulted in  $\chi^2(521) = 2003.31$ ,  $p < .0001$ , which indicates that model fit is significantly improved by the inclusion of the covariates.

The two-class solution resulted in one relatively large class ( $n = 1162$ ) and one relatively small class ( $n = 151$ ). Although this information does not indicate the appropriateness of model fit, it is important to examine the average probability of class assignment to determine the appropriateness of fit. The probability of assignment to latent classes was also examined to determine the quality of the two-class solution. The probability of assignment data are presented in Table 20, with the number and proportion of individuals assigned to each latent class. It was found that the average probability for latent class membership is high, ranging from .91 to .98, while the probability of being assigned to a different latent class is .09, ranging from 0.00 to 0.06 for all classes. This evidence supports the two-class solution.

Table 20

Average Latent Class Probabilities for Latent Class Membership (Row) by Most Likely Latent Class (Column)  
for Latent Class Analysis Model A Two-Class Solution

Class	<i>N</i>	%	Most Likely Latent Class	
			1	2
1	1162	88.5	0.98	
2	151	11.5	0.09	0.91

Note. *N* = 1313.

The latent ICCS factors were allowed to covary using the mixture modeling technique, but those correlations were held constant across the classes. The latent factor correlation matrix estimated by Mplus in generating the class solution is presented in Table 21. The factor intercorrelations among the ICCS latent factors were all moderate, ranging from  $r = .20$  to  $.59$ , and significant at  $p < .0001$ .

Table 21

Innovation-Capacity Climate Survey (ICCS) Factor Intercorrelations Resulting from Latent Profile Analysis  
Model A Two-Class Solution

Latent Factor	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1. Meaningful Work	1.00								
F2. Risk Taking	0.42	1.00							
F3. Customer Orientation	0.40	0.45	1.00						
F4. Agile Decision Making	0.42	0.59	0.45	1.00					
F5. Business Intelligence	0.24	0.31	0.43	0.38	1.00				
F6. Open Communication	0.34	0.52	0.30	0.51	0.23	1.00			
F7. Empowerment	0.29	0.37	0.27	0.36	0.20	0.42	1.00		
F8. Business Planning	0.24	0.35	0.39	0.43	0.47	0.28	0.24	1.00	
F9. Learning Organization	0.31	0.39	0.50	0.42	0.44	0.29	0.25	0.46	1.00

Note. *N* = 1313. \*All correlations significant at  $p < .0001$ .

The final consideration for the appropriateness of model fit is the interpretability of the latent profiles. For each latent factor score, the mean and standard error of the mean for each class are presented in Table 22. These mean profiles with 95% confidence intervals were graphed. This depiction of latent factor score profiles is presented in Figure 6. The two latent profiles are clearly distinct in terms of means factor scores and profile shape. Between the two profiles, no mean confidence intervals overlap.

The first latent class ( $n = 1162$ ) has a relatively flat profile that sits just above average for all of the ICCS latent factor scores. The second latent class ( $n = 151$ ) sits below average for all ICCS latent factor scores. Although the profile for the second latent class is also relatively flat, two scores for the second latent class are dramatically lower, including the scores for Open Communication (F6) and Empowerment (F7).

Table 22

Summary Statistics for Latent Profile Analysis Model A Class Solution for Innovation-Capacity Climate Survey (ICCS) Factor Scores

Latent Factors	Latent Profile Analysis (LPA) Model A Class Solution			
	Latent Class1 ( $n = 1162$ )		Latent Class 2 ( $n = 151$ )	
	<i>M</i>	SE	<i>M</i>	SE
F1. Meaningful Work	0.23	0.02	-0.64	0.10
F2. Risk Taking	0.26	0.03	-0.80	0.10
F3. Customer Orientation	0.16	0.03	-0.49	0.11
F4. Agile Decision Making	0.27	0.03	-0.69	0.09
F5. Business Intelligence	0.12	0.03	-0.28	0.07
F6. Open Communication	0.28	0.03	-1.10	0.09
F7. Empowerment	0.34	0.02	-1.57	0.09
F8. Business Planning	0.16	0.03	-0.26	0.08
F9. Learning Organization	0.13	0.03	-0.34	0.09

Note. Latent Factors are ICCS Latent Factor Scores.

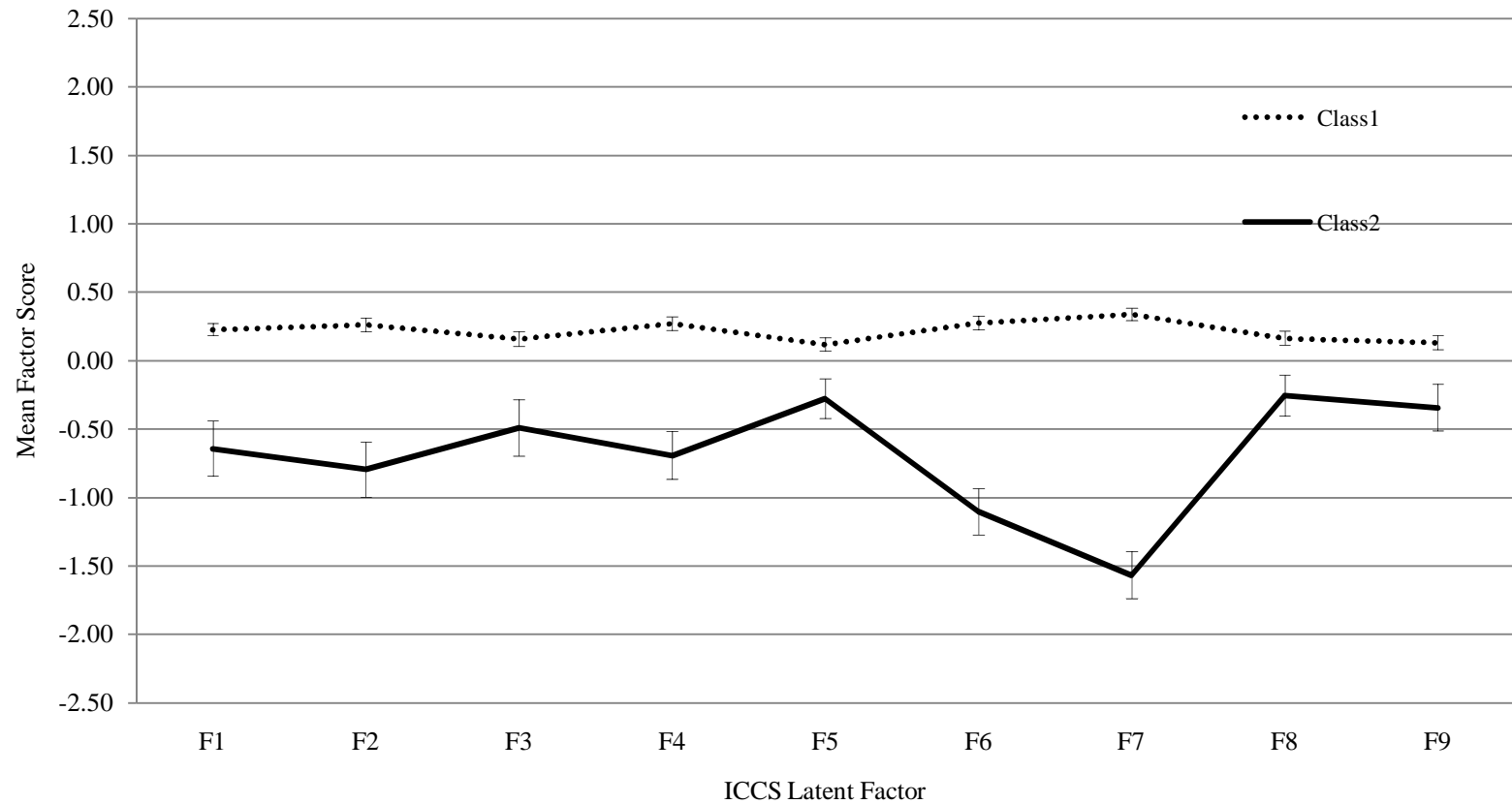


Figure 6. Latent Profiles Latent Profile Analysis Model A for the Innovation-Capacity Climate Survey (ICCS) with Outliers Removed.  $N = 1313$ . F1 is Meaningful Work, F2 is Risk Taking, F3 is Customer Orientation, F4 is Agile Decision Making, F5 is Business Intelligence, F6 is Open Communication, F7 is Empowerment, F8 is Business Planning, and F9 is Learning Organization. Error bars represent 95% confidence intervals.



Next, I investigated the contribution of the individual demographic covariates. Estimates, standard errors, significance values, and logistic regression odds ratio results for each covariate entered into LPA Model A are presented in Table 23. I found that company membership and organizational level were significantly related to the latent class solution while functional unit and organizational tenure were unrelated.

Table 23

Demographic Covariate Tests of Significance for Latent Profile Analysis (LPA) Model A, Two-Class Solution

Statistics	Number of Classes ( <i>k</i> )			
	$\beta$	<i>SE</i>	Odds Ratio	<i>p</i>
Company	.21	.10	1.24	.04
Functional Unit	-.04	.05	1.00	.94
Organizational Level	.84	.21	2.31	.00
Organizational Tenure	.02	.07	1.02	.83

Note. *N* = 1313. All covariates included in model.

Based on all of the available information, I conclude that the two-class solution for LPA Model A appropriately fits the data. The statistical indices of fit suggest that the two-factor class is the best-fitting model; classification probabilities are acceptably high; factor intercorrelations are moderate; and the profiles are interpretable. Two of the covariates, company membership and organizational level, were significantly related to the solution. For lack of more information to describe these two latent classes, the first latent class (*n* = 1162) is tentatively labeled “Above Average” and the second (*n* = 151) tentatively labeled “Below Average.” LPA Model B attempts to replicate these findings using a different technique. The results for LPA Model B are presented in the next section.

**LPA Model B.** In LPA Model B nine latent factor scores were used to identify latent classes of individuals who share a latent profile on the ICCS. I specified the Mplus analysis type as mixture. The ICCS latent factor scores were free to correlate with the constraint that the correlations be held constant across classes. The theoretical model tested by LPA Model A is presented in Figure 7.

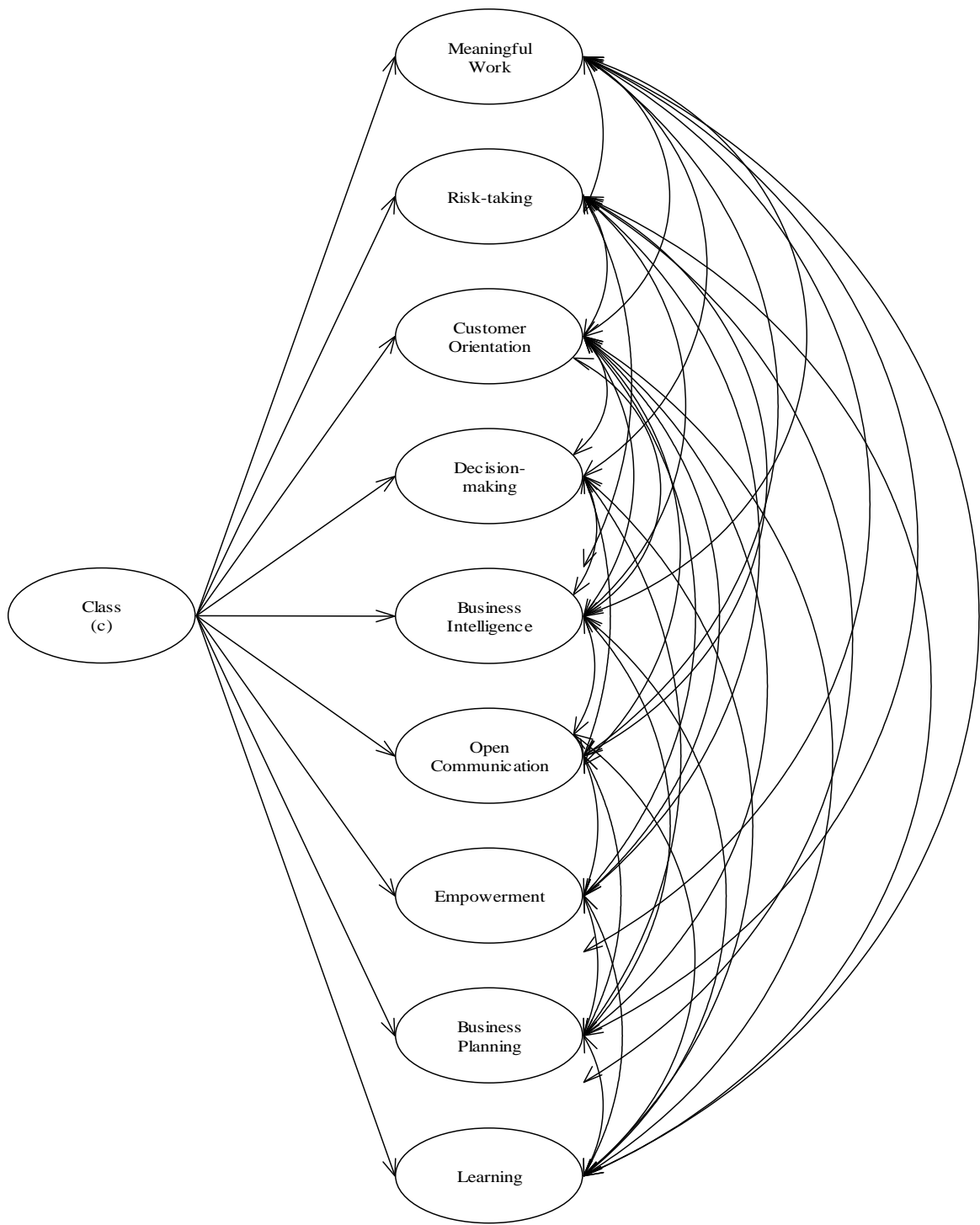


Figure 7. Innovation-Capacity Climate Survey (ICCS) Latent Profile Analysis (LPA) Mixture Model with Continuous Variables that Correlate within Class.

LPA Model B did not require cases to be eliminated due to missing demographic covariate data. As a result, the data from all companies could be used in this analysis and the sample size is larger ( $N = 1752$ ). The LPA iteration procedures described above were replicated on the new dataset ( $N = 1752$ ) in the attempt to generate a class solution that adequately fits the data in the absence of demographic covariate influence. The indicators of fit for LPA Model B are presented in Table 24.

Table 24

Latent Profile Analysis (LPA) Model B Fit Statistics

Statistics	Number of Classes ( $k$ )				
	2	3	4	5	6
Akaike Information Criterion (AIC)	25730.38	25565.90	25502.90	25438.65	25421.39
Bayesian Information Criterion (BIC)	26080.37	25970.57	25962.26	25952.69	25990.12
Entropy	0.88	0.80	0.82	0.84	0.83
Vuong-Lo-Mendell-Rubin Likelihood Ratio (for $k$ versus $k - 1$ classes) $p$ value	0.00	0.00	0.05	0.16	0.38

Note.  $N = 1752$ .

The indicators of fit for these data are not as certain as the indicators were for the data that included covariates. While the AIC drops with each successive iteration of the model, the BIC value decreases with each iteration until the five-class solution, at which point it increases for the six-class solution. The Entropy value for the five-class model suggests it is a better fit than the three-class model. However, the explicit test of model fit  $p$  value indicates that the three-class model is a better fit. Additional information about the best-fitting model is evaluated for the three- and five-class models. First, the latent class sizes and average probabilities of latent class membership for the three- and five-class solutions are presented in Table 25.

For the three-class solution, the class sizes range from 12% to 62% of the sample; the probabilities for correct classification range from  $p = .87$  to  $.93$ ; and the average probability of misclassification is  $p = .05$ . For the five-class solution, two small classes ( $n = 57$ ) account for three percent of the sample size while the other

three classes range from 14% to 56% of the sample. The probabilities for correct classification range from  $p = .82$  to  $.93$ ; the average probability for misclassification is  $p = .03$ . Although the evidence related to latent class membership and probability for latent class membership does not clearly distinguish which solution is preferable, the small sizes of two classes for the five-class solution may be of concern.

The factor intercorrelations for LPA Model B three-class and five-class solutions are presented in Table 26. While the average factor correlation for the three-class model is  $r = .28$ , the average correlation for the five-class solution is  $r = .22$ . For comparative purposes, the average factor correlation for the five-class solution that included outliers was  $r = .27$ . For all three solutions, the factor correlations are low to moderate and are all statistically significant.

Table 25

Average Latent Class Probabilities for Latent Class Membership (Row) by Most Likely Latent Class (Column) for Latent Class Analysis Model B Three- and Five-Class Solutions

			Most Likely Latent Class				
Class	<i>N</i>	Proportion	1	2	3	4	5
Three-Class model							
1	449	.26	.88				
2	215	.12	.09	.87			
3	1088	.62	.05	.01	.93		
Five-Class Model							
1	57	.03	.90				
2	249	.14	.05	.82			
3	410	.23	.00	.04	.89		
4	979	.56	.00	.01	.04	.93	
5	57	.03	.00	.00	.00	.16	.85

Note.  $N = 1752$ .

Table 26

## Innovation-Capacity Climate Survey (ICCS) Factor Intercorrelations for Three- and Five-Class Solutions

Latent Factor	F1	F2	F3	F4	F5	F6	F7	F8	F9
Three-Class solution									
F1. Meaningful Work	1.00								
F2. Risk Taking	.34	1.00							
F3. Customer Orientation	.34	.37	1.00						
F4. Agile Decision Making	.34	.45	.36	1.00					
F5. Business Intelligence	.18	.23	.36	.30	1.00				
F6. Open Communication	.20	.30	.17	.29	.12	1.00			
F7. Empowerment	.23	.26	.20	.25	.14	.25	1.00		
F8. Business Planning	.19	.28	.33	.35	.43	.16	.17	1.00	
F9. Learning Organization	.24	.30	.43	.32	.38	.15	.16	.39	.00
Five-Class Solution									
F1. Meaningful Work	1.00								
F2. Risk Taking	.28	1.00							
F3. Customer Orientation	.30	.33	1.00						
F4. Agile Decision Making	.28	.39	.32	1.00					
F5. Business Intelligence	.14	.18	.33	.25	1.00				
F6. Open Communication	.14	.23	.13	.22	.06	1.00			
F7. Empowerment	.15	.18	.15	.17	.07	.14	1.00		
F8. Business Planning	.14	.21	.29	.29	.37	.08	.09	1.00	
F9. Learning Organization	.21	.26	.40	.28	.34	.10	.10	.34	1.00

Note.  $N = 1752$ . \*All correlations significant at  $p < .005$ .

Comparisons of means and standard errors of the means for the three- and five-class solutions are presented in Tables 27 and 28, respectively. Mean profile plots, including 95% confidence intervals for the means for the LPA Model B three- and five-class solutions are presented in Figures 8 and 9, respectively.

For the three-class solution, only one class is distinct on all data points. Latent class 3 sits above average with none of its confidence intervals overlapping the other two class profiles. Latent Profiles 1 and 2 both sit below the mean. The confidence intervals around each mean indicate that they are not distinct for Factor 5, 8, or 9 (Business Intelligence, Business Planning, or Learning Organization, respectively).

Table 27

Summary Statistics for Latent Profile Analysis Model B Three-Class Solution on Innovation-Capacity Climate Survey (ICCS) Factor Scores

Latent Factor	Latent Profile Analysis (LPA) Model B, Three-Class Solution					
	1		2		3	
	(n = 449)		(n = 215)		(n = 1088)	
	<i>M</i>	SE	<i>M</i>	SE	<i>M</i>	SE
F1. Meaningful Work	-0.24	0.05	-0.63	0.10	0.33	0.02
F2. Risk Taking	-0.40	0.05	-0.86	0.10	0.47	0.03
F3. Customer Orientation	-0.17	0.05	-0.50	0.10	0.28	0.03
F4. Agile Decision Making	-0.41	0.04	-0.77	0.09	0.46	0.03
F5. Business Intelligence	-0.15	0.05	-0.27	0.07	0.22	0.03
F6. Open Communication	-0.67	0.03	-1.81	0.11	0.63	0.02
F7. Empowerment	-0.13	0.03	-1.55	0.09	0.47	0.03
F8. Business Planning	-0.22	0.05	-0.31	0.07	0.27	0.03
F9. Learning Organization	-0.20	0.05	-0.39	0.08	0.27	0.03

Note. Latent Factors are ICCS Latent Factor Scores.

Table 28

Summary Statistics for Latent Profile Analysis Model B Five-Class Solution on Innovation-Capacity Climate Survey (ICCS) Factor Scores

Latent Factor	Latent Profile Analysis (LPA) Model B, Five-Class Solution									
	1		2		3		4		5	
	(n = 57)		(n = 249)		(n = 410)		(n = 979)		(n = 57)	
	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>
F1. Meaningful Work	-1.28	0.33	-0.34	0.10	-0.27	0.06	0.33	0.03	0.92	0.08
F2. Risk Taking	-1.43	0.23	-0.55	0.10	-0.42	0.05	0.46	0.03	1.23	0.09
F3. Customer Orientation	-0.63	0.20	-0.37	0.09	-0.16	0.06	0.25	0.03	1.05	0.13
F4. Agile Decision Making	-1.28	0.21	-0.49	0.10	-0.44	0.05	0.44	0.03	1.27	0.12
F5. Business Intelligence	-0.42	0.15	-0.22	0.09	-0.17	0.06	0.19	0.03	1.16	0.19
F6. Open Communication	-1.89	0.18	-0.77	0.12	-0.68	0.04	0.61	0.02	1.53	0.11
F7. Empowerment	-2.27	0.22	-1.09	0.11	-0.12	0.05	0.48	0.02	1.55	0.05
F8. Business Planning	-0.48	0.16	-0.28	0.08	-0.25	0.05	0.23	0.03	1.42	0.29
F9. Learning Organization	-0.53	0.17	-0.31	0.08	-0.19	0.06	0.24	0.03	1.08	0.22

Note. Latent Factors are ICCS Latent Factor Scores.

Interpretation of the three- and five-class solutions was relatively straightforward. For the three-class solution, three profiles were clearly differentiated by level on each factor score with only one extreme score (Empowerment factor score for Class 2).

The labels tentatively assigned to the classes of the three-class solution are:

- Latent Class 1<sub>3</sub> – Average
- Latent Class 2<sub>3</sub> – Below Average
- Latent Class 3<sub>3</sub> – Above Average

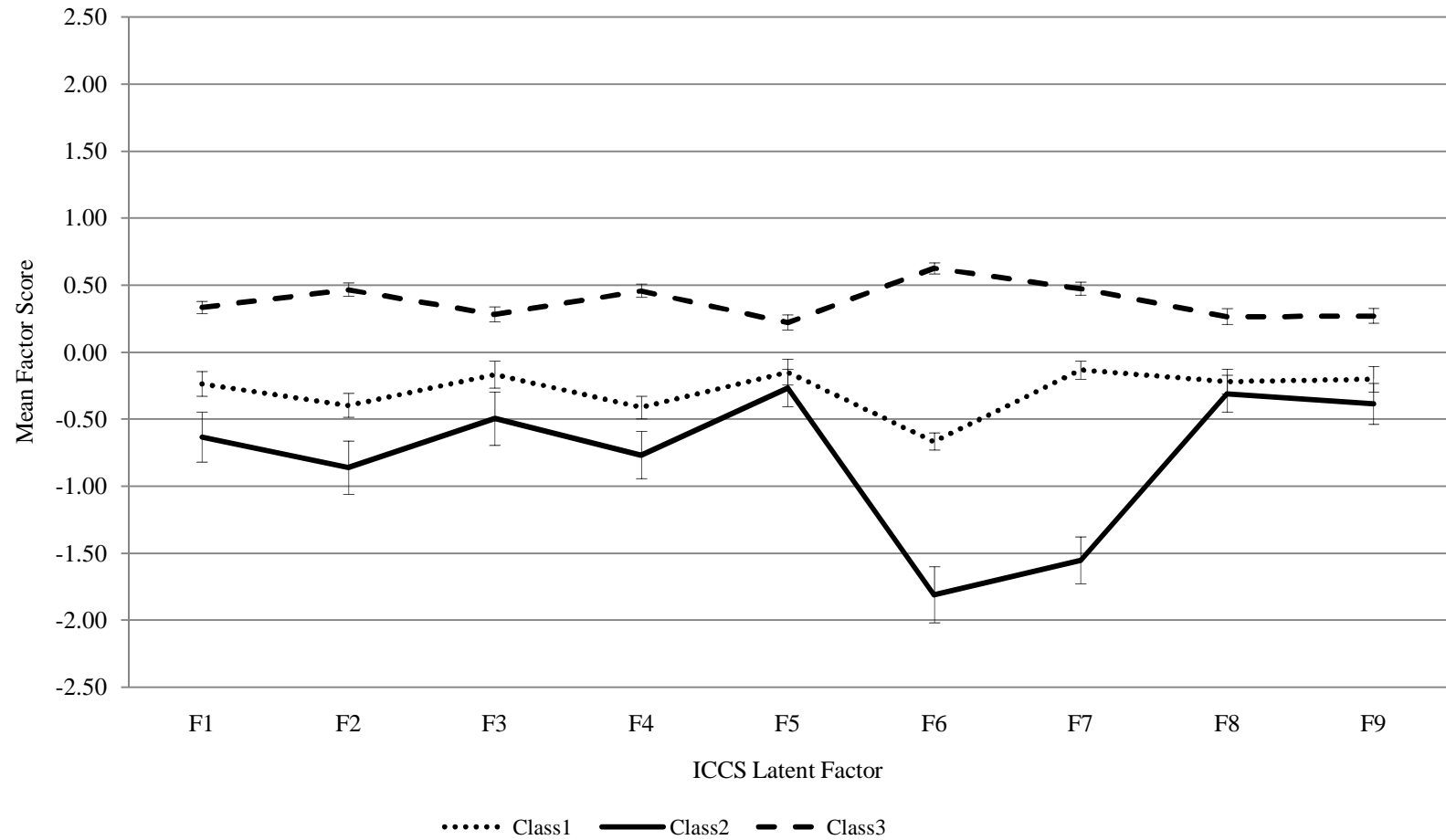


Figure 8. Latent Profiles for Model B, Three-Class Innovation-Capacity Climate Survey (ICCS) with Outliers Removed.  $N = 1752$ . F1 is Meaningful Work, F2 is Risk Taking, F3 is Customer Orientation, F4 is Agile Decision Making, F5 is Business Intelligence, F6 is Open Communication, F7 is Empowerment, F8 is Business Planning, and F9 is Learning Organization.



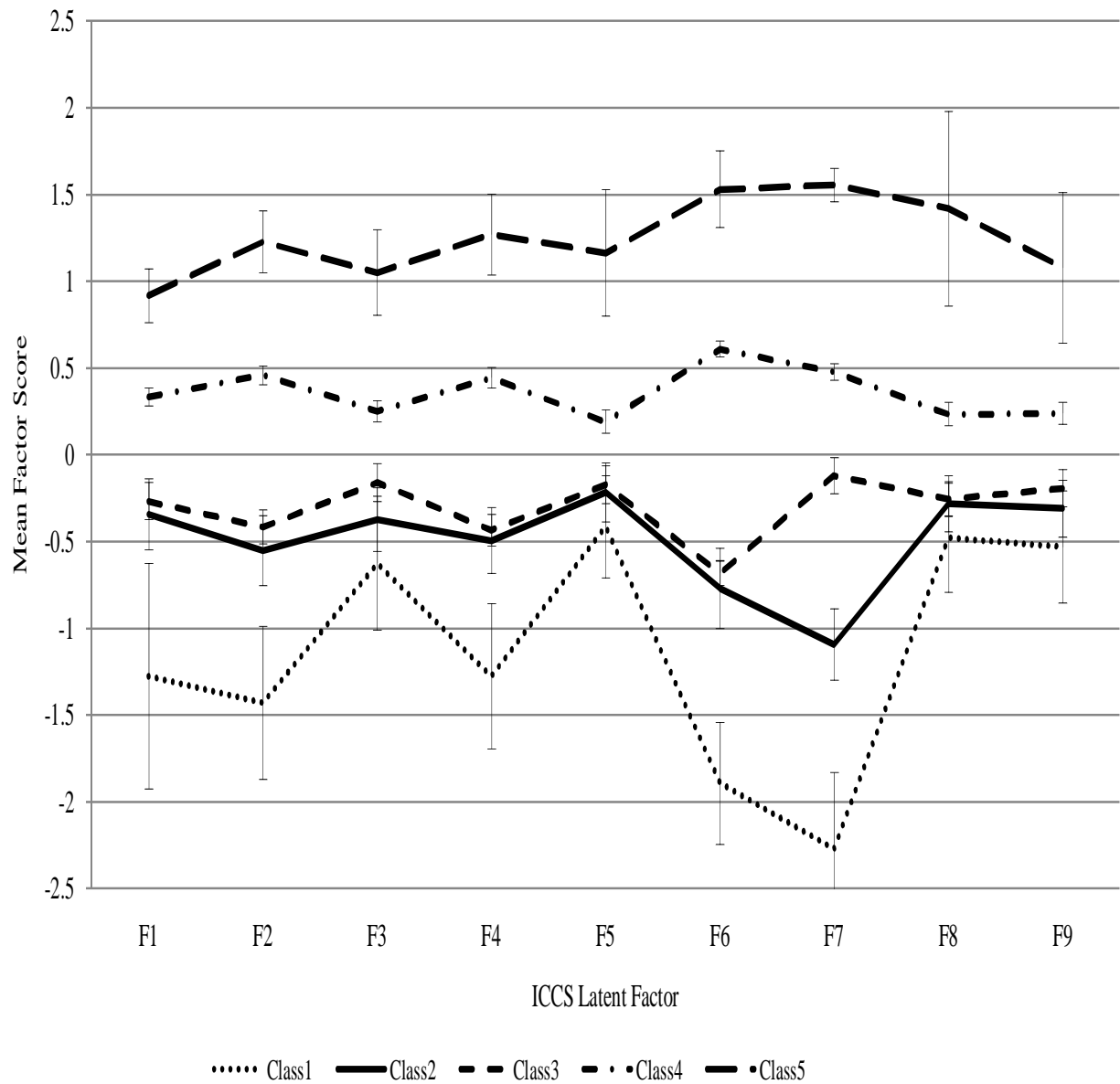


Figure 9. Latent Profiles for Model B Five-Class Innovation-Capacity Climate Survey (ICCS) with Outliers Removed.

$N = 1752$ . F1 is Meaningful Work, F2 is Risk Taking, F3 is Customer Orientation, F4 is Agile Decision Making, F5 is Business Intelligence, F6 is Open Communication, F7 is Empowerment, F8 is Business Planning, and F9 is Learning Organization

The five-class solution contains two classes whose profiles sit above the mean. The confidence intervals for these means suggest that these classes are distinguished by their scores on all factors from each other and from the other three profiles. The three remaining profiles sit below the mean. Although they are distinct from each other on some means, these profiles are messy, which suggests that the classes are distinguished by relatively few mean differences.

The five-class solution profiles were also differentiated by mean scores. The labels tentatively assigned to the five-class solution are:

- Latent Class 1<sub>5</sub> – Low Across the Board
- Latent Class 2<sub>5</sub> – Below Average
- Latent Class 3<sub>5</sub> – Below Average, Low Empowerment
- Latent Class 4<sub>5</sub> – Above Average
- Latent Class 5<sub>5</sub> – High across the Board

A comparison of class assignments between the three- and five-class solutions is presented in Table 29. For this comparison,  $\chi^2(8) = 2678.54, p < .0001$ , indicating that the relationship between the two solutions is statistically significant. Of the 215 classified into the “Below Average” class for the three-class solution, 100% were also classified into the “Low across the Board” or “Below Average” profile for the five-class solution. For the 1088 classified into the “Above Average” class in the three-class solution, 93.47% were also classified into the “Above Average” or “High across the Board” classes of the five-class solution. The majority of cases classified into the “Average” class of the three factor solution were classified into the “Below Average, Low Empowerment” latent class of the five-class solution. These findings suggest that the two- and five-class solutions are related statistically and conceptually.

I examined the relationships among the demographic covariates and the latent profile solutions using multinomial logistic regression methods and SAS’s Proc Logistic program (SAS Institute, 2002 – 2003). All covariates (company membership, functional unit membership, organizational level, and organizational tenure) were dummy-coded into a set of indicator variables for each category of the demographic variables. I entered the dummy-coded variables into the logistic regression equation to predict the LPA Model B class membership.

Individual equations were calculated for each demographic variable using a block entry method. For each logistic equation, the reference category selected was the category with the highest proportion of cases.

Table 29

Comparison of Latent Profile Analysis (LPA) Model B Latent Class Assignments for Three- and Five-Class Solutions for ICCS Factor Scores

Five-Class Solution Class	Three-Class Solution Class		
	1 <sub>3</sub> Average	2 <sub>3</sub> Below Average	3 <sub>3</sub> Above Average
1 <sub>5</sub> Low Across the Board	1	56	0
2 <sub>5</sub> Below Average	31	159	59
3 <sub>5</sub> Below, Low Empowerment	398	0	12
4 <sub>5</sub> Above Average	19	0	960
5 <sub>5</sub> High Across the Board	0	0	57

Note.  $N = 1752$ .

For each equation, a significant global test statistic would indicate that the categories combine to predict class membership significantly. The global significance test results for the multinomial logistic regression analyses, in which three- and five-class membership are independently predicted by demographic covariates, are presented in Table 30.

For both the three- and five-class solutions, all parameters were statistically significant, indicated by the Likelihood Ratio and Wald  $\chi^2$  tests of model fit. This result indicates that company membership, functional unit membership, organizational level, and organizational tenure are each independently related to both class solutions generated when Company A is included in the latent profile analysis.

To ensure that these results were approximately equivalent to the results generated for LPA Model A, the logistic regression was conducted separately for this model using the same method described above. The global tests of model fit for each demographic covariate are presented in Table 31.

Table 30

Logistic Regressions Global Tests of Significance Results for Latent Profile Analysis (LPA) Model B, Three- and Five-Class Solutions.

Demographic Covariate	Likelihood Ratio $\chi^2$	<i>df</i>	<i>p</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Three-Class Model						
Company	48.13	4	<.0001	46.31	4	<.0001
Functional Unit	46.40	9	<.0001	43.17	9	<.0001
Organizational Level	51.28	3	<.0001	45.86	3	<.0001
Organizational Tenure	12.69	5	0.0264	12.04	5	0.0342
Five-Class Model						
Company	45.83	4	<.0001	45.29	4	<.0001
Functional Unit	41.24	9	<.0001	39.18	4	<.0001
Organizational Level	56.03	3	<.0001	53.12	3	<.0001
Organizational Tenure	13.72	5	0.018	13.46	5	0.019

Note. *N* = 1752.

Table 31

Logistic Regressions Global Tests of Significance Results for Latent Profile Analysis (LPA) Model A

Demographic Covariate	Likelihood Ratio	<i>df</i>	<i>p</i>	Wald	<i>df</i>	<i>p</i>
Company	37.74	3	<.0001	37.55	3	<.0001
Functional Unit	24.34	9	0.0038	16.28	9	0.0613
Organizational Level	49.57	3	<.0001	34.23	3	<.0001
Organizational Tenure	10.98	5	0.0519	6.06	5	0.3000

Note. *N* = 1313.

For LPA Model A, the Likelihood Ratio  $\chi^2$  and Wald  $\chi^2$  for company and organizational role were statistically significant, although these tests for organizational tenure were not statistically significant. These results yield conclusions that duplicate those previously reached for LPA Model A. However, for functional unit, the Likelihood Ratio  $\chi^2$  and Wald  $\chi^2$  yield different conclusions. The Likelihood Ratio  $\chi^2$  suggests a statistically significant relationship for functional unit membership, while the Wald  $\chi^2$  does not. As Mplus also uses the Wald statistic, using this test alone leads to the same conclusions about the relationships among latent class membership and the demographic covariates.

Because the global tests parallel the information considered for LPA Model A and model-fitting was not a goal of this analysis, the results for each category were not of interest. However, parameters and significance tests for these variables at the category level are provided in Appendix E.

**Comparison of LPA Model A to LPA Model B Class Solutions.** Between LPA Model A and LPA Model B, three possible latent class solutions have been generated. For LPA Model A, a two-class solution with two significant demographic covariates was selected.

For LPA Model B, a three-class solution that is significantly related to all demographic covariates and a five-class model that is significantly related to all demographic covariates were selected. If the profiles are stable, there should be a high degree of correspondence among the assignments to all three solutions for the cases that are redundant across analyses ( $N = 1313$ ). I examined these relationships in an expectancy table, which is presented in Table 32.

The comparison of the LPA Model A two-class solution yielded  $\chi^2(2) = 1044.61, p < .0001$ , indicating a significant relationship between the two solutions. Of the 1162 cases classified into the first latent class for LPA Model A (Above Average), 98.71% were classified into the first or third latent class for LPA Model B (Average and Above Average, respectively). Of the 151 cases classified in the second latent class of LPA Model A, 90.72% were also classified into the second latent class of LPA Model B (Below Average). In addition to the statistical data confirming the strong relationship between the two solutions, the class assignments between the two models appear to be conceptually congruent as well.

Table 32

Latent Class Assignments Among the LPA Model A and LPA Model B Solutions

LPA Model B Solution	Class Assignment / Label	LPA Model A Class Assignment	
		1 - Above Average	2 - Below Average
Three-Class Solution	1 - Average	316	1
	2 - Below Average	15	137
	3 - Above Average	831	13
Five-Class Solution	1 - Low Across the Board	0	45
	2 - Below Average	69	103
	3 - Below Average, Low Empowerment	287	0
	4 - Above Average	757	3
	5 - High Across the Board	49	0

Note.  $N = 1313$ . Data in cells are observed counts.

The comparison of the two-class solution for LPA Model A and the five-class solution for LPA Model B is also statistically significant,  $\chi^2(4) = 877.66, p < .0001$ . However, examination of the relationship is not conceptually congruent for all classes. Of the 1162 cases assigned to the first Latent Class for LPA Model A (Above Average), 30.64% were also classified into the second and third latent classes for the LPA Model B solution (Below Average, and Below Average with Low Empowerment). The remaining 69.36% were classified in the Average and Above Average latent classes.

**Implications of LPA Results for Research Questions.** The LPA analyses provided some information related to first and second research questions posed in this study. Research Question 1 asked, “Which latent profiles of climate for innovation perceptions are used to distinguish classes or groups of individuals?” In addition to the specific profiles presented earlier, some general findings answer this question. For all of the latent class solutions identified, profiles were generated that generally classified individuals based on their overall factor score relative to the mean. In other words, most of the ICCS profiles were relatively flat, with some being above, others below, and still others at approximately average.

With the identification of more profiles, such as comparing LPA Model B three- and five-class solutions to the two-class solution identified for LPA Model A, increasing variability among profiles is observed. In addition, with the inclusion of a new subset of data (Company A) in Model B, more profiles were identified and less certainty about which class solution was correct was apparent in the indices of fit.

Two possibilities exist for why different numbers of profiles were generated for Model A and Model B. First, the presence of covariates in the LPA analysis for Model A may have led to clearer profile identification. In short, more data points to use in generating profile solutions may result in fewer solutions and greater certainty about the correct solution. Alternately, the addition of new data (Company A) to the Model B analysis may have led to new profiles being discovered. It is also possible that a combination of these two occurrences led to the differing number of profiles. The analyses I conducted do not answer this question definitively.

Despite differences in the numbers of profiles, relatively high agreement in the classification of individuals to classes relative to average was found among all profile solutions considered. While all profile solutions generated classes with profiles that could be interpreted, the solution for Model A was most clearly distinct. Only for this solution were all means clearly distinguished between the two classes.

Research Question 2 asked, “Which demographic covariates contribute most to the formation and identification of latent profiles for climate (e.g., company, functional unit membership, organizational level, and organizational tenure)?” Only the results from the LPA Model A solution answer this question directly. I found that company membership and organizational level contributed significantly to the classification of individuals to latent classes based on latent ICCS scores. The results for LPA Model B suggest that all demographic covariates were related to class solution, but were not used in the actual formation of classes. If functional unit data had been available for Company A, this question may have been answered by the analysis including that subsample.

### **Multivariate Analysis of Variance (MANOVA)**

**MANOVA: Relative Importance of Situational or Individual Difference Covariates.** I specified a MANOVA in which the nine latent ICCS factor scores were predicted from the demographic covariates. This

model included main effects for each demographic variable and two-way interaction effects for company with functional unit membership, organizational unit membership, and organizational tenure. I conducted this analysis to determine the relative importance of each covariate as a situational or individual difference variable in the prediction of perceptions of the climate for innovation. Due to unequal cell sizes, the Type III Sums of Squares are used for this analysis. The multivariate significance test results are presented in Table 33.

Table 33

Multivariate Tests for Multivariate Analysis of Variance (MANOVA) for Prediction of ICCS Factor Scores from Demographic Covariates.

Effect	Wilks' $\Lambda$	$F$	Hyp $df$	Error $df$	$p$	Partial $\eta^2$	Noncentrality Parameter	Power
Intercept	0.995	1.042	9	1802	0.404	0.005	9.38	0.53
Company	0.974	1.326	36	6755	0.092	0.007	44.72	0.98
Function	0.937	1.468	81	11654	0.004	0.007	85.24	1.00
Level	0.943	3.936	27	5263	0.000	0.019	103.44	1.00
Tenure	0.967	1.342	45	8064	0.063	0.007	54.00	0.99
Company * Function	0.870	1.087	234	15397	0.174	0.015	241.08	1.00
Company * Level	0.926	1.295	108	13131	0.022	0.009	113.01	1.00
Company * Tenure	0.899	1.070	180	14884	0.249	0.012	176.40	1.00

Note.  $N = 327$ .  $F$  statistics are exact. Power estimate was computed using  $\alpha = .05$ . Hotelling's Trace, and Pillai's Trace  $p$  values as Wilks'  $\Lambda$ . Roy's Greatest Root yielded significant results for all effects in the model.

Only three effects in the model were statistically significant according to the Wilks'  $\Lambda$  criterion, including the main effect for functional unit membership: Wilks'  $\Lambda = .937$ ,  $F(81, 11654) = 1.468$ ,  $p = .004$ ; the main effect for organizational level,  $\Lambda = .943$ ,  $F(27, 5263) = 3.936$ ,  $p < .0001$ ; and the interaction between company membership and level, Wilks'  $\Lambda = .870$ ,  $F(234, 13131) = 1.295$ ,  $p = .022$ . It should be noted that for all effects in the model, other than the intercept, observed power was sufficiently high for these analyses,



ranging from power = .98 to 1.00. Therefore, it is assured that the probability of correctly identifying non-significant effects is acceptably high. The univariate ANOVA results for the between-subjects effects of the significant predictors are presented in Table 34.

The between-subjects results indicate significant prediction of all ICCS factors for the overall model and for the main effect of function. For organizational level, the between-subjects results indicate significant prediction of Meaningful Work (Factor 1), Risk Taking (Factor 2), Agile Decision Making (Factor 4), Open Communication (Factor 6), Empowerment (Factor 7), and Business Planning (Factor 8). For the Company X Level interaction effect, only Business Intelligence (Factor 5) and Business Planning (Factor 8) were significant. It should be noted that for many between-subjects effects, the observed power was insufficient to ensure correct rejection of the null hypothesis.

The detailed nature of these relationships was not a primary concern in the present research study. However, the estimated marginal means for ICCS factor scores for the significant MANOVA effects of functional unit membership, organizational level, and the interaction of company and level are presented in Appendix F.

**Implications of MANOVA results for Research Questions.** The results of the MANOVA provide information to answer Research Questions 3, 4, and 5. Research Question 3 asked, “To what extent are perceptions of the climate for innovation influenced by situational/environmental factors (e.g., company membership, functional unit membership within company, organizational level within company, and organizational tenure within company)?”

Although company was a significant contributor to the identification of classes in the LPA, the nature of its relationship (direct or in interaction with other variables) was unclear. For the MANOVA, only one situational variable, organizational level within organization (Company X Level) was statistically significant. The univariate results indicate that this interaction only predicted two of the nine ICCS dimensions, Business Planning and Business Intelligence.

Table 34

Between Subjects Effects for Multivariate Analysis of Variance (MANOVA) to Predict ICCS Latent Scores from Demographic Factors

Dependent Variable	Type III Sum of Squares	<i>df</i>	<i>MS</i>	<i>F</i>	<i>p</i>	Partial $\eta^2$	Noncentrality Parameter	Power
Corrected Model								
F1. Meaningful Work	134.26	79	1.70	2.254	0.00	0.090	178.08	1.00
F2. Risk Taking	157.63	79	2.00	2.340	0.00	0.093	184.88	1.00
F3. Customer Orientation	185.62	79	2.35	2.774	0.00	0.108	219.13	1.00
F4. Agile Decision Making	176.80	79	2.24	2.826	0.00	0.110	223.22	1.00
F5. Business Intelligence	142.14	79	1.80	2.424	0.00	0.096	191.53	1.00
F6. Open Communication	179.54	79	2.27	2.714	0.00	0.106	214.40	1.00
F7. Empowerment	145.16	79	1.84	2.222	0.00	0.088	175.53	1.00
F8. Business Planning	135.93	79	1.72	2.140	0.00	0.085	169.05	1.00
F9. Learning Organization	187.76	79	2.38	2.958	0.00	0.114	233.65	1.00
Function								
F1. Meaningful Work	17.26	9	1.92	2.543	0.01	0.012	22.89	0.94
F2. Risk Taking	26.37	9	2.93	3.436	0.00	0.017	30.93	0.99
F3. Customer Orientation	18.13	9	2.01	2.378	0.01	0.012	21.40	0.92
F4. Agile Decision Making	22.94	9	2.55	3.218	0.00	0.016	28.97	0.98
F5. Business Intelligence	22.28	9	2.48	3.336	0.00	0.016	30.02	0.99

Table 34 Continued.

F6. Open Communication	15.44	9	1.72	2.048	0.03	0.010	18.44	0.87
F7. Empowerment	16.21	9	1.80	2.178	0.02	0.011	19.60	0.89
F8. Business Planning	15.60	9	1.73	2.156	0.02	0.011	19.40	0.89
F9. Learning Organization	16.25	9	1.81	2.246	0.02	0.011	20.22	0.91
Level								
F1. Meaningful Work	8.98	3	2.99	3.971	0.01	0.007	11.91	0.84
F2. Risk Taking	7.42	3	2.47	2.899	0.03	0.005	8.70	0.69
F3. Customer Orientation	3.61	3	1.20	1.421	0.24	0.002	4.26	0.38
F4. Agile Decision Making	7.29	3	2.43	3.067	0.03	0.005	9.20	0.72
F5. Business Intelligence	1.96	3	0.65	0.880	0.45	0.001	2.64	0.24
F6. Open Communication	11.87	3	3.96	4.726	0.00	0.008	14.18	0.90
F7. Empowerment	13.68	3	4.56	5.513	0.00	0.009	16.54	0.94
F8. Business Planning	10.47	3	3.49	4.339	0.01	0.007	13.02	0.87
F9. Learning Organization	4.14	3	1.38	1.716	0.16	0.003	5.15	0.45
Company*Level								
F1. Meaningful Work	5.72	12	0.48	0.632	0.82	0.004	7.59	0.38
F2. Risk Taking	6.37	12	0.53	0.622	0.83	0.004	7.47	0.37
F3. Customer Orientation	8.83	12	0.74	0.868	0.58	0.006	10.42	0.52

Table 34 Continued.

F4. Agile Decision Making	11.94	12	1.00	1.256	0.24	0.008	15.07	0.72
F5. Business Intelligence	16.95	12	1.41	1.904	0.03	0.012	22.85	0.91
F6. Open Communication	9.41	12	0.78	0.936	0.51	0.006	11.23	0.56
F7. Empowerment	9.19	12	0.77	0.926	0.52	0.006	11.11	0.56
F8. Business Planning	17.71	12	1.48	1.836	0.04	0.012	22.03	0.90
F9. Learning Organization	12.48	12	1.04	1.294	0.22	0.009	15.53	0.74

Note. Power calculated based on  $\alpha = .05$ .

Research Question 4 asked, “To what extent are perceptions of the climate for innovation influenced by individual differences (e.g., functional unit membership across companies, organizational level across companies, and organizational tenure across companies)?” Two of these effects, functional unit membership across organizations and organizational level across organizations, were significant. While organizational tenure across organizations was considered a proxy for age, it was not significant in any of the analyses. Functional membership and organizational level were conceptualized as individual differences as proxies for occupational role or choice.

Research Question 5 asked, “If both situation and individual difference variables are found to be important to perceptions of climate, is one type of variable dominant?” Based on the MANOVA results, it appears that individual differences are more predictive of climate for innovation perception than are situational influences, in terms of the number of effects that are found to be significant, the number of individual dimensions of climate predicted by each, and the effect sizes corresponding to those predictions.

#### **Multivariate Analysis of Covariance (MANCOVA)**

**MANCOVA: Predictive Utility of LPA Class Solutions.** To test the utility of latent class identification for the prediction of important organizational outcomes, MANCOVA techniques were employed. This stage of the analysis was conducted on the target sample only ( $N = 383$ ) and only cases with complete data for all variables were included. A separate MANCOVA was specified for each of the three latent class solutions (LPA Model A, LPA Model B three-class solution, and LPA Model B five-class solution) identified above. For each MANCOVA conducted, six dependent variables (latent factor scores for A-O, C-O, A-I, N-I, IWB-C and IWB-I) were predicted from one independent categorical variable (LPA class solution) and nine covariates (ICCS latent factor scores). Two of the originally intended covariates (N-O and C-I) were not considered during this phase of the analysis due to maximal and internal consistency reliability concerns.

**MANCOVA: LPA Model A.** Sample statistics by LPA Model A class membership are presented in Table 35. The representation of each class in the target sample is unequal, with Class 1 ( $n = 304$ ) accounting for 93% of the cases and Class 2 ( $n = 23$ ) accounting for the remaining 7% of cases. Due to the large discrepancy in the independent variable (class membership), Type III Sums of Squares were used.

Table 35

Summary Statistics for LPA Model A Covariate and Dependent Variable Factor Scores.

Latent Factor	Class 1 - Above Average ( <i>n</i> = 304)		Class 2 - Below Average ( <i>n</i> = 23)	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
F1. Meaningful Work	0.13	0.66	-1.12	0.99
F2. Risk Taking	0.20	0.77	-1.13	0.76
F3. Customer Orientation	-0.02	0.86	-0.97	0.82
F4. Agile Decision Making	0.23	0.75	-0.94	0.71
F5. Business Intelligence	0.03	0.82	-0.32	0.73
F6. Open Communication	0.33	0.73	-1.08	0.68
F7. Empowerment	0.29	0.60	-1.64	0.55
F8. Business Planning	0.10	0.84	-0.26	0.87
F9. Learning Organization	-0.03	0.84	-0.39	0.85
A-O	0.12	0.84	-1.00	1.25
C-O	0.03	0.89	0.02	0.92
A-I	0.00	0.89	-0.15	0.95
N-I	0.08	0.88	-0.71	1.02
IWB - C	-0.02	0.91	0.01	0.98
IWB - I	-0.02	0.92	-0.03	0.90

Note. Data are for target sample with complete data (*N* = 327). A-O, C-O, and N-O are affective, continuous, and normative commitment to the organization, respectively. A-I, C-I, and N-I are affective, continuous, and normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation IWBs, respectively.

The results of the multivariate tests of significance for the independent variable (class membership) and the nine covariates (ICCS factor scores); along with estimates of effect size, noncentrality parameters, and observed power, are presented in Table 36. Only the independent variable (class membership) and one covariate yielded significant multivariate results, for class membership Wilks'  $\Lambda = .959$ ,  $F(6, 311) = 2.227$ ,  $p = .040$ , and for Meaningful Work (Factor 1) Wilks'  $\Lambda = .936$ ,  $F(6, 311) = 3.535$ ,  $p = .002$ .

Table 36

Multivariate Tests for Multivariate Analysis of Covariance (MANCOVA) for Latent Profile Analysis (LPA) Model A.

Effect	Wilks' $\Lambda$	$F$	Hyp $df$	Error $df$	$p$	Partial $\eta^2$	Noncentrality Parameter	Power
Intercept	0.966	1.847	6	311	0.090	0.034	11.08	0.69
F1. Meaningful Work	0.936	3.535	6	311	0.002	0.064	21.21	0.95
F2. Risk Taking	0.981	0.981	6	311	0.438	0.019	5.89	0.39
F3. Customer Orientation	0.987	0.69	6	311	0.658	0.013	4.14	0.27
F4. Agile Decision Making	0.990	0.519	6	311	0.794	0.010	3.11	0.21
F5. Business Intelligence	0.991	0.448	6	311	0.847	0.009	2.69	0.18
F6. Open Communication	0.978	1.187	6	311	0.313	0.022	7.12	0.47
F7. Empowerment	0.982	0.934	6	311	0.471	0.018	5.60	0.37
F8. Business Planning	0.990	0.549	6	311	0.770	0.010	3.30	0.22
F9. Learning Organization	0.975	1.327	6	311	0.245	0.025	7.96	0.52
Class	0.959	2.227	6	311	0.040	0.041	13.36	0.78

Note.  $N = 327$ .  $F$  statistics are exact. Power estimate was computed using  $\alpha = .05$ . Hotelling's Trace, Pillai's Trace, and Roy's Greatest Root yielded same  $p$  values as Wilks'  $\Lambda$ .

Given these results, it appears that class membership for the LPA Model A class solution does contribute to the prediction of important organizational outcomes beyond the contribution of the latent factor scores used to identify the classes. The power estimates are highly variable, ranging from observed power = .18 to .95. Only for Meaningful Work (Factor 1) does power fall within acceptable limits (power > .80). For Class, power approaches the acceptable range. However, for this variable and all other covariates, the chance of making a Type II error is not sufficiently low. Although all but two of the predictors in this model are non-significant, the findings of non-significance should be interpreted cautiously as there is not sufficient power to ensure that such findings are truly non-significant. For this reason, no conclusions that the eight other covariates in the model are not significantly related to the outcomes are drawn.

The univariate ANOVA results provide additional information about the significant effects for class membership and Meaningful Work (Factor 1). The between-subjects results for the overall corrected model, Meaningful Work (Factor 1) and Class Membership are presented in Table 37. For three of the six dependent variables, the between-subjects effects were significant for the overall model. These include A-O  $F(10) = 14.41$ ,  $p < .0001$ , C-O  $F(10) = 5.63$ ,  $p < .0001$ , and N-I  $F(10) = 3.591$ ,  $p < .0001$ . The covariate Meaningful Work (Factor 1) is a significant predictor of A-O,  $F(1) = 10.67$ ,  $p = .031$ , of A-I,  $F(1) = 6.52$ ,  $p = .01$ , and of IWB-C  $F(1) = 5.29$ ,  $p = .022$ . Class membership is a significant predictor of only one of the dependent variables, N-I, for which  $F(11) = 4.50$ ,  $p = .035$ .

As found for the multivariate results, the observed power was low for most comparisons, so the probability of correctly rejecting a null hypothesis is not sufficient for these comparisons. The results should be interpreted carefully and no conclusions drawn about the lack of a relationship between any of the other comparisons tested. For the corrected model,  $R^2$  and Adjusted  $R^2$  values were calculated for each dependent variable, so that for A-O  $R^2 = .31$  and Adjusted  $R^2 = .29$ ; for C-O,  $R^2 = .15$  and Adjusted  $R^2 = .12$ ; for A-I,  $R^2 = .04$  and Adjusted  $R^2 = .01$ ; for N-I  $R^2 = .10$  and Adjusted  $R^2 = .07$ ; for IWB-C  $R^2 = .03$  and Adjusted  $R^2 = .00$ ; and for IWB-I  $R^2 = .04$  and Adjusted  $R^2 = .01$ . The  $R^2$  and Adjusted  $R^2$  values obtained indicate non-prediction of a large proportion of the variation in the dependent variables.

The estimated marginal means, standard deviations, and 95% confidence intervals for the six dependent variable by each class are presented in Table 38. The estimated marginal means provide an estimate for the dependent variables when the levels of the covariates are held constant. Given the larger size of Class 1, it is not surprising that the standard errors of the marginal means are smaller for this class, and therefore the confidence intervals for Class 1 are narrower. For Class 2, the confidence intervals are generally broad, ranging from low negative factor scores to high positive factor scores for some variables. To illustrate these results, the estimated marginal means for Class 1 and Class 2 are presented in Figure 10.



Table 37

Between Subjects Effects for Latent Profile Analysis (LPA) Model A Multivariate Analysis of Covariance

Dependent Variable	Type III Sum of Squares	df	Mean Square	F	p	Partial $\eta^2$	Noncentrality Parameter	Power
Corrected Model								
A-O	86.36	10	8.64	14.414	0.000	0.313	144.14	1.00
C-O	35.12	10	3.51	5.629	0.000	0.151	56.29	1.00
A-I	10.49	10	1.05	1.339	0.208	0.041	13.39	0.68
N-I	27.75	10	2.78	3.591	0.000	0.102	35.91	0.99
IWB-C	9.01	10	0.90	1.077	0.380	0.033	10.77	0.57
IWB-I	10.79	10	1.08	1.296	0.232	0.039	12.96	0.67
F1. Meaningful Work								
A-O	6.03	1	6.03	10.067	0.002	0.031	10.07	0.89
C-O	0.01	1	0.01	0.018	0.892	0.000	0.02	0.05
A-I	5.10	1	5.10	6.515	0.011	0.020	6.52	0.72
N-I	0.28	1	0.28	0.361	0.548	0.001	0.36	0.09
IWB-C	4.42	1	4.42	5.287	0.022	0.016	5.29	0.63
IWB-I	4.86	1	4.86	5.835	0.016	0.018	5.84	0.67
Class								
A-O	0.11	1	0.11	0.179	0.673	0.001	0.18	0.07
C-O	0.00	1	0.00	0.001	0.971	0.000	0.00	0.05
A-I	0.03	1	0.03	0.031	0.860	0.000	0.03	0.05
N-I	3.47	1	3.47	4.495	0.035	0.014	4.50	0.56
IWB-C	0.46	1	0.46	0.549	0.459	0.002	0.55	0.11
IWB-I	0.12	1	0.12	0.149	0.699	0.000	0.15	0.07

Note. Power calculated based on  $\alpha = .05$ . A-O and C-O are affective and continuous commitment to the organization, respectively, A-I and N-I are normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation innovative work behaviors, respectively.

Table 38

Estimated Marginal Means by Latent Profile Analysis (LPA) Model A Classes with Nine Innovation-Capacity Climate Survey (ICCS) Factor Score Covariates

DV	Class 1				Class 2			
	<i>M</i>	<i>SE</i>	<i>LL</i>	<i>UL</i>	<i>M</i>	<i>SE</i>	<i>LL</i>	<i>UL</i>
A-O	0.052	0.046	-0.039	0.142	-0.049	0.226	-0.493	0.395
C-O	0.049	0.047	-0.044	0.141	0.04	0.23	-0.413	0.493
A-I	-0.011	0.053	-0.114	0.093	0.037	0.258	-0.47	0.545
N-I	0.068	0.052	-0.035	0.171	-0.506	0.256	-1.01	-0.002
IWB-C	-0.037	0.054	-0.144	0.07	0.172	0.267	-0.353	0.696
IWB-I	-0.027	0.054	-0.134	0.079	0.081	0.266	-0.442	0.605

Note. DV is dependent variable. A-O and C-O are affective and continuous commitment to the organization, respectively, A-I and N-I are normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation innovative work behaviors, respectively.

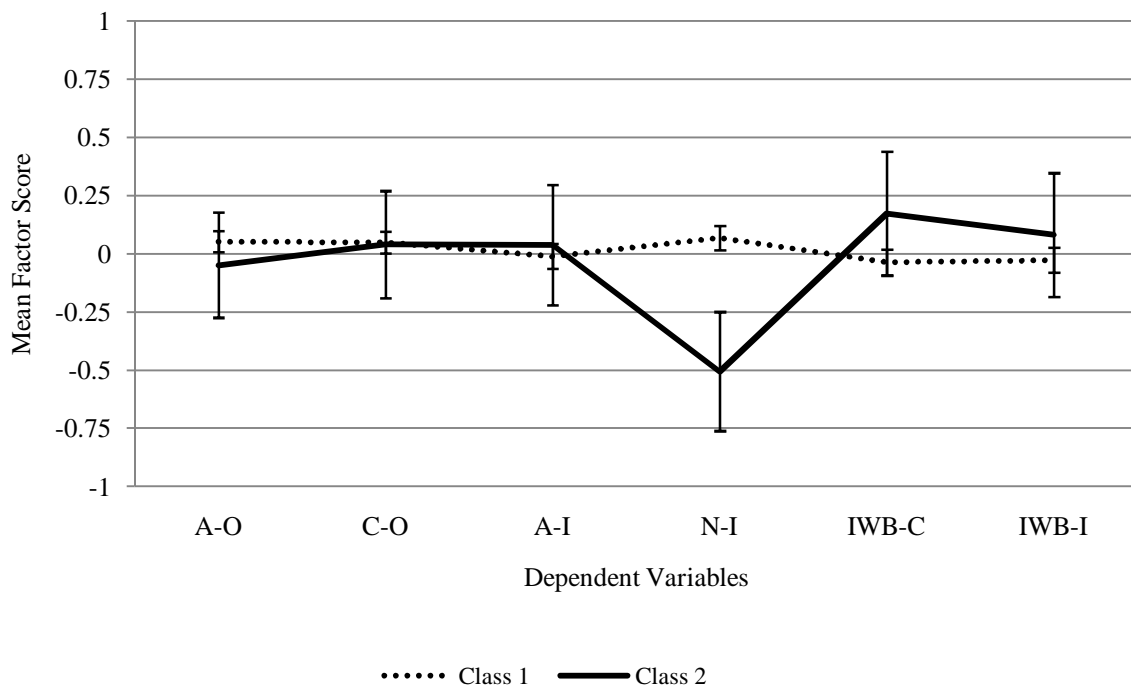


Figure 10. Estimated Marginal Means of Dependent Variables by Latent Profile Analysis (LPA) Model A.

For Class 1, the mean profile of the dependent variables is relatively flat, sits at approximately zero, and has narrow confidence intervals around each mean. For Class 2, there is greater variability in mean scores, with some clearly falling above and below average, but also very broad confidence intervals that, in most cases, overlap with those for Class 1. One exception to this is for the dependent variable N-I (Normative Commitment to Innovation). For Class 2, this score is clearly lower than for Class 1 and the confidence intervals around each mean do not overlap. It appears that the only dependent variable predicted by class membership is N-I.

**MANCOVA: LPA Model B Three-Class Solution.** I repeated the MANCOVA on the LPA Model B three-class solution. The only difference between the two analyses is the independent factor, in this case, the three-class solution generated by Model B. Summary statistics related to the data and class membership are presented in Table 39.

For the MANCOVA involving the LPA Model B three-class solution, the results of the multivariate tests of significance for the independent variable (class membership) and the nine covariates (ICCS factor scores), along with estimates of effect size, non-centrality parameters, and observed power, are presented in Table 40. Only one covariate yielded significant multivariate results, Meaningful Work (Factor 1) Wilks'  $\Lambda = .936$ ,  $F(6, 311) = 3.775$ ,  $p = .001$ . The analysis of primary interest was found to be nonsignificant, Class Membership, Wilks'  $\Lambda = .964$ ,  $F(12, 658) = 1.107$ ,  $p = .43$ , *n.s.*

Given these results, it appears that class membership for the LPA Model B three-class solution does not contribute to the prediction of important organizational outcomes beyond the contribution of the latent factor scores used to identify the classes. However, the power associated with most of the comparisons was not sufficient to assure correct rejection of the null hypothesis. Although the statistical tests for class and eight of the covariates are not statistically significant, firm conclusions that there is no true relationship cannot be drawn. In light of the finding of non-significance for this model, however, no additional analyses, such as the univariate ANOVA results or estimated marginal means were considered.

**MANCOVA: LPA Model B Five-Class Solution.** The MANCOVA analyses conducted on the LPA Model A and Model B three-class solutions were repeated on the LPA Model B five-class solution. The only difference between these analyses is the independent variable, in this case, the five-class solution generated

by Model B. Summary statistics related to the data and class membership are presented in Table 41. One guideline for sample size in MANCOVA is that the number of cases in a cell must exceed the number of dependent variables. Because Class 1 has only six cases, and there are six dependent variables, Class 1 was excluded from this analysis.

Table 39

Summary Statistics for LPA Model B Three-Class Solution, Covariate and Dependent Variable Factor Scores.

Variable	Class 1 (n = 69)		Class 2 - (n = 31)		Class 3 - (n = 246)	
	M	SD	M	SD	M	SD
Meaningful Work	-0.25	0.72	-0.98	0.94	0.26	0.59
Risk Taking	-0.29	0.72	-1.15	0.70	0.37	0.70
Customer Orientation	-0.28	0.80	-1.07	0.76	0.11	0.85
Agile Decision Making	-0.30	0.68	-0.98	0.61	0.42	0.67
Business Intelligence	-0.20	0.77	-0.42	0.65	0.11	0.81
Open Communication	-0.64	0.46	-1.10	0.56	0.64	0.49
Empowerment	-0.15	0.47	-1.52	0.54	0.46	0.51
Business Planning	-0.07	0.74	-0.44	0.81	0.20	0.84
Learning Organization	-0.35	0.76	-0.62	0.85	0.10	0.82
A-O	-0.18	1.06	-0.99	1.11	0.23	0.71
C-O	0.11	0.96	-0.06	0.89	0.02	0.86
A-I	-0.15	0.99	-0.08	0.94	0.03	0.86
N-I	-0.09	0.94	-0.45	1.03	0.09	0.89
IWB - C	-0.14	0.85	0.11	0.97	0.01	0.94
IWB - I	-0.20	0.91	0.10	0.83	0.02	0.95

Note. A-O and C-O are affective and continuous commitment to the organization, respectively, A-I and N-I are normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation innovative work behaviors, respectively.

Table 40

Multivariate Tests for Multivariate Analysis of Covariance (MANCOVA) for Latent Profile Analysis (LPA) Model B Three-Class Solution.

Effect	Wilks' $\Lambda$	$F$	Hyp $df$	Error $df$	$p$	Partial $\eta^2$	Noncentrality Parameter	Power
Intercept	0.984	0.879	6	329	0.511	0.016	5.27	0.35
F1. Meaningful Work	0.936	3.775	6	329	0.001	0.064	22.65	0.96
F2. Risk Taking	0.986	0.780	6	329	0.586	0.014	4.68	0.31
F3. Customer Orientation	0.984	0.890	6	329	0.502	0.016	5.34	0.35
F4. Agile Decision Making	0.993	0.366	6	329	0.900	0.007	2.20	0.16
F5. Business Intelligence	0.988	0.658	6	329	0.683	0.012	3.95	0.26
F6. Open Communication	0.980	1.116	6	329	0.353	0.020	6.70	0.44
F7. Empowerment	0.989	0.603	6	329	0.728	0.011	3.62	0.24
F8. Business Planning	0.990	0.528	6	329	0.787	0.010	3.17	0.21
F9. Learning Organization	0.986	0.801	6	329	0.570	0.014	4.80	0.32
Class	0.964	1.017	12	658	0.431	0.018	12.21	0.60

Note.  $N = 327$ .  $F$  statistics are exact. Power estimate was computed using  $\alpha = .05$ . Hotelling's Trace, Pillai's Trace and Roy's Greatest Root yielded same  $p$  values as Wilks'  $\Lambda$ .

For the MANCOVA involving the LPA Model B five-class solution, the results of the multivariate tests of significance for the independent variable (class membership) and the nine covariates (ICCS factor scores), along with estimates of effect size, non-centrality parameters, and observed power, are presented in Table 42. The effect for Class was significant, Wilks'  $\Lambda = .902$ ,  $F(18, 911) = 1.880$ ,  $p = .014$ . Only one of the nine covariates yielded significant multivariate results, Meaningful Work (Factor 1) Wilks'  $\Lambda = .951$ ,  $F(6, 332) = 2.765$ ,  $p = .012$ . Given these results, it appears that class membership for the LPA Model B five-class solution does contribute to the prediction of important organizational outcomes beyond the contribution of the latent factor scores used to identify the classes.

The power associated with the significant multivariate results was acceptably high, above power = .80 for both variables. Only two of the other power estimates approach the acceptable range, for the model intercept

power = .68 and for Open Communication (Factor 6) power = .67. Consequently, findings of non-significance are interpreted cautiously as there is not sufficient power to ensure that such findings are truly non-significant. For this reason, no conclusions that the eight other covariates in the model are not significantly related to the outcomes are drawn.

Table 41

Summary Statistics for LPA Model B Five-Class Solution, Covariate and Dependent Variable Factor Scores.

Variable	Class 1 ( <i>n</i> = 6)		Class 2 ( <i>n</i> = 39)		Class 3 ( <i>n</i> = 61)		Class 4 ( <i>n</i> = 231)		Class 5 ( <i>n</i> = 9)	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
F1	-2.23	0.64	-0.62	0.71	-0.28	0.74	0.26	0.54	1.07	0.68
F2	-1.89	0.42	-0.81	0.72	-0.31	0.68	0.37	0.66	1.31	0.71
F3	-1.60	0.36	-0.80	0.80	-0.30	0.78	0.09	0.84	1.06	0.70
F4	-1.65	0.32	-0.68	0.65	-0.33	0.64	0.40	0.62	1.46	0.73
F5	-0.83	0.65	-0.38	0.70	-0.22	0.77	0.09	0.76	1.40	0.54
F6	-1.98	0.45	-0.79	0.44	-0.65	0.42	0.63	0.41	1.72	0.36
F7	-2.47	0.36	-1.13	0.39	-0.13	0.39	0.46	0.41	1.66	0.27
F8	-0.50	0.73	-0.41	0.85	-0.14	0.69	0.19	0.81	1.39	0.55
F9	-0.99	0.46	-0.45	0.87	-0.43	0.72	0.08	0.79	1.17	0.77
A-O	-2.40	0.50	-0.62	1.06	-0.17	1.00	0.25	0.68	0.41	0.81
C-O	-0.09	1.09	-0.09	0.93	0.17	0.92	0.01	0.86	0.24	0.99
A-I	-0.41	0.39	-0.03	1.12	-0.21	0.83	0.02	0.86	0.74	1.12
N-I	-0.59	0.65	-0.37	1.20	-0.06	0.78	0.06	0.87	1.04	1.07
IWB - C	-0.01	1.27	0.08	0.97	-0.33	0.86	0.03	0.91	0.68	0.96
IWB - I	0.05	0.97	0.05	0.94	-0.37	0.93	0.04	0.92	0.81	0.80

Note. F1 is Meaningful Work, F2 is Risk Taking, F3 is Customer Orientation, F4 is Agile Decision Making, F5 is Business Intelligence, F6 is Open Communication, F7 is Empowerment, F8 is Business Planning, and F9 is Learning Organization. A-O and C-O are affective and continuous commitment to the organization, respectively, A-I and N-I are normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation innovative work behaviors, respectively.

Table 42

Multivariate Tests for Multivariate Analysis of Covariance (MANCOVA) for Latent Profile Analysis (LPA) Model B Five-Class Solution.

Effect	Wilks' $\Lambda$	$F$	Hyp $df$	Error $df$	$p$	Partial $\eta^2$	Noncentrality Parameter	Power
Intercept	0.967	1.830	6	322	0.093	0.033	10.98	0.68
F1. Meaningful Work	0.951	2.765	6	322	0.012	0.049	16.59	0.88
F2. Risk Taking	0.985	0.795	6	322	0.574	0.015	4.77	0.32
F3. Customer Orientation	0.985	0.842	6	322	0.538	0.015	5.05	0.33
F4. Agile Decision Making	0.992	0.409	6	322	0.873	0.008	2.45	0.17
F5. Business Intelligence	0.989	0.598	6	322	0.732	0.011	3.59	0.24
F6. Open Communication	0.968	1.800	6	322	0.099	0.032	10.80	0.67
F7. Empowerment	0.988	0.679	6	322	0.667	0.012	4.07	0.27
F8. Business Planning	0.992	0.429	6	322	0.859	0.008	2.58	0.18
F9. Learning Organization	0.987	0.717	6	322	0.636	0.013	4.30	0.28
Class	0.902	1.880	18	911.239	0.014	0.034	31.88	0.96

Note.  $N = 340$ .  $F$  statistics are exact. Power estimate was computed using  $\alpha = .05$ . Hotelling's Trace, Pillai's Trace and Roy's Greatest Root yielded same  $p$  values as Wilks'  $\Lambda$ .

The univariate ANOVA results provide additional information about the significant effects for class membership and Meaningful Work (Factor 1). The between-subjects results for the overall corrected model, Meaningful Work (Factor 1) and Class Membership are presented in Table 43. For five of the six dependent variables the between-subjects effects were significant for the overall model. These include A-O  $F(12) = 8.37$ ,  $p < .0001$ , A-I  $F(12) = 2.18$ ,  $p = .012$ , N-I  $F(12) = 2.98$ ,  $p = .001$ , IWB-C  $F(12) = 2.176$ ,  $p = .013$ , and IWB-I  $F(12) = 2.44$ ,  $p = .01$ .

Table 43

Between Subjects Effects for Latent Profile Analysis (LPA) Model B Five-Class Solution Multivariate Analysis of Covariance (MANCOVA).

Dependent Variable	Type III Sum of Squares	df	Mean Square	F	p	Partial $\eta^2$	Noncentrality Parameter	Power
Corrected Model								
A-O	57.73	12	4.81	8.373	0.000	0.235	100.48	1.00
C-O	14.78	12	1.23	1.623	0.084	0.056	19.48	0.84
A-I	20.41	12	1.70	2.179	0.012	0.074	26.15	0.95
N-I	28.46	12	2.37	2.979	0.001	0.099	35.75	0.99
IWB-C	21.43	12	1.79	2.176	0.013	0.074	26.12	0.95
IWB-I	22.65	12	1.89	2.244	0.010	0.076	26.93	0.95
F1. Meaningful Work								
A-O	4.98	1	4.98	8.670	0.003	0.026	8.67	0.84
C-O	1.53	1	1.53	2.021	0.156	0.006	2.02	0.29
A-I	3.87	1	3.87	4.960	0.027	0.015	4.96	0.60
N-I	0.87	1	0.87	1.087	0.298	0.003	1.09	0.18
IWB-C	2.57	1	2.57	3.135	0.078	0.009	3.14	0.42
IWB-I	2.70	1	2.70	3.208	0.074	0.010	3.21	0.43
Class								
A-O	3.24	3	1.08	1.881	0.133	0.017	5.64	0.49
C-O	0.68	3	0.23	0.300	0.825	0.003	0.90	0.11
A-I	7.61	3	2.54	3.249	0.022	0.029	9.75	0.74
N-I	4.24	3	1.41	1.773	0.152	0.016	5.32	0.46
IWB-C	9.38	3	3.13	3.811	0.010	0.034	11.43	0.82
IWB-I	9.70	3	3.24	3.846	0.010	0.034	11.54	0.82

Note. Power calculated based on  $\alpha = .05$ . A-O and C-O are affective and continuous commitment to the organization, respectively, A-I and N-I are normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation innovative work behaviors, respectively.



The covariate Meaningful Work (Factor 1) is a significant predictor of A-O,  $F(1) = 8.67$ ,  $p = .003$ , and A-I,  $F(1) = 4.96$ ,  $p = .027$ . Class membership is a significant predictor of three of the dependent variables, A-I, for which  $F(3) = 3.25$ ,  $p = .022$ , IWB-C for which  $F(3) = 3.81$ ,  $p = .01$ , and IWB-I for which  $F(12) = 3.85$ ,  $p = .01$ . Although all remaining univariate results were non-significant, the observed power was low for most comparisons, so the probability of correctly rejecting a null hypothesis is not sufficient for these comparisons. The results should be interpreted carefully and no conclusions drawn about the lack of a relationship between any of the other comparisons tested.

For the corrected model,  $R^2$  and Adjusted  $R^2$  values were calculated for each dependent variable so that for A-O  $R^2 = .24$  and Adjusted  $R^2 = .21$ ; for C-O,  $R^2 = .06$  and Adjusted  $R^2 = .02$ ; for A-I,  $R^2 = .07$  and Adjusted  $R^2 = .04$ ; for N-I  $R^2 = .10$  and Adjusted  $R^2 = .07$ ; for IWB-C  $R^2 = .07$  and Adjusted  $R^2 = .04$ ; and for IWB-I  $R^2 = .08$  and Adjusted  $R^2 = .04$ . The  $R^2$  and Adjusted  $R^2$  values obtained indicate non-prediction of a large proportion of the variation in the dependent variables.

The estimated marginal means, standard deviations, and 95% confidence intervals for the six dependent variable by each class are presented in Table 44. The estimated marginal means, presented in Figure 11, provide an estimate for the dependent variables when the levels of the covariates are held constant.

Table 44

Estimated Marginal Means by Latent Profile Analysis (LPA) Model B Five-Class Solution with Nine Innovation-Capacity Climate Survey (ICCS) Factor Score Covariates

DV	<i>M</i>	<i>SE</i>	<i>LL</i>	<i>UL</i>
Class 2 ( $n = 39$ )				
A-O	-0.16	0.19	-0.54	0.22
C-O	-0.12	0.22	-0.55	0.32
A-I	-0.21	0.23	-0.65	0.23
N-I	-0.20	0.23	-0.64	0.25
IWB-C	0.16	0.23	-0.29	0.62
IWB-I	0.13	0.23	-0.33	0.59

Table 44 Continued.

Class 3 ( <i>n</i> = 61)				
A-O	0.09	0.15	-0.21	0.38
C-O	0.00	0.17	-0.34	0.34
A-I	-0.39	0.17	-0.73	-0.05
N-I	0.06	0.18	-0.28	0.41
IWB-C	-0.47	0.18	-0.82	-0.12
IWB-I	-0.47	0.18	-0.83	-0.12
Class 4 ( <i>n</i> = 231)				
A-O	0.13	0.07	0.00	0.26
C-O	0.05	0.08	-0.09	0.20
A-I	0.09	0.08	-0.06	0.24
N-I	0.01	0.08	-0.14	0.16
IWB-C	0.06	0.08	-0.10	0.21
IWB-I	0.05	0.08	-0.10	0.21
Class 5 ( <i>n</i> = 9)				
A-O	-0.29	0.31	-0.91	0.32
C-O	0.35	0.36	-0.36	1.05
A-I	0.99	0.36	0.27	1.70
N-I	0.75	0.37	0.03	1.48
IWB-C	0.57	0.37	-0.17	1.30
IWB-I	0.68	0.38	-0.06	1.43

Note. DV is the dependent variable. A-O and C-O are affective and continuous commitment to the organization, respectively, A-I and N-I are normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation innovative work behaviors, respectively.

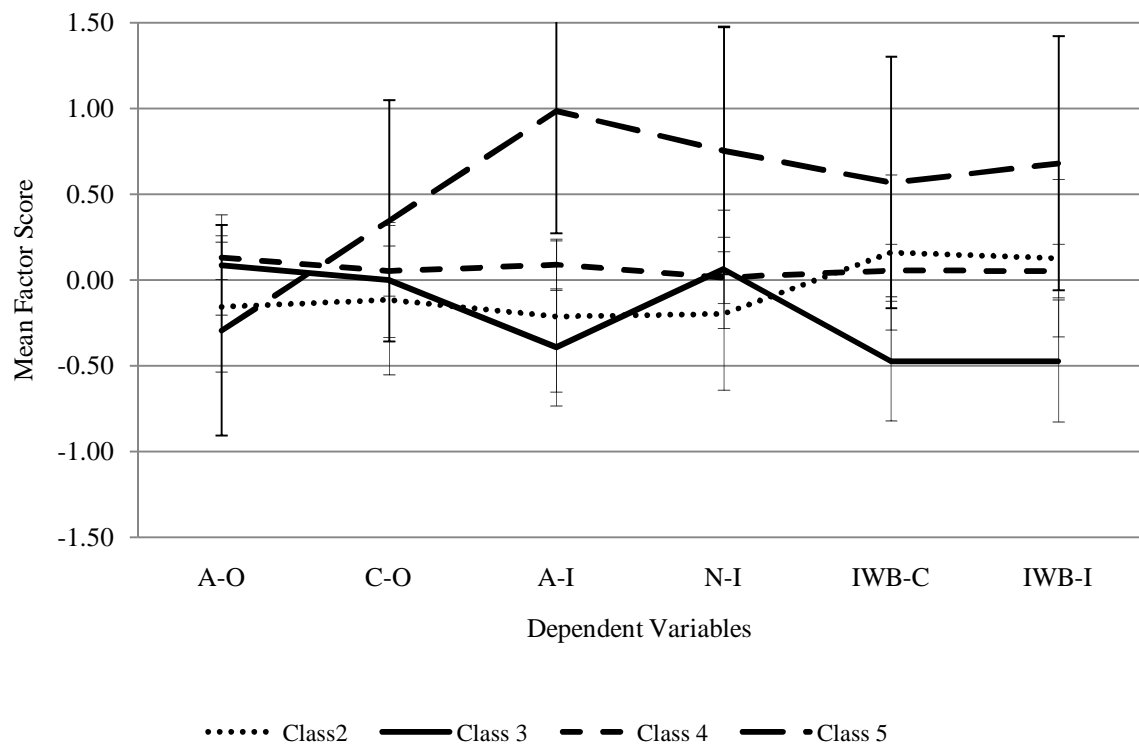


Figure 11. Estimated Marginal Means of Dependent Variables by Latent Profile Analysis (LPA) Model B Five-Class Solution (with Class 1 omitted).

A-O and C-O are affective and continuous commitment to the organization, respectively, A-I and N-I are normative commitment to innovation, respectively. IWB-C and IWB-I are creative and implementation innovative work behaviors, respectively.

As indicated by the between-subjects effects, the greatest variation found among the profiles occurs on the A-I, IWB-C and IWB-I dependent variables. Class 2 and Class 5, the smaller classes, have the broadest confidence intervals. However, despite this, Class 5 is clearly differentiated from the other three classes, sitting well above average across most of the means, and with particularly high scores on A-I, N-I, IWB-C and IWB-I. The other class that is clearly unique among those presented here is Class 3, demonstrating clearly lower scores than the other classes on several of the scores, and for innovative work behavior in particular. Class 2 and Class 4 demonstrate relatively flat profiles on the dependent variables.

**Implications of MANCOVA Results for Research Questions.** The MANCOVA analyses were conducted to determine whether latent class membership predicts important organizational criteria beyond the scores used to identify the profiles. In essence, this analysis attempted to discern whether the latent classes represent something more than ICCS factor scores.

Research Question 6 asked, “Can affective, normative, and continuance commitment to the organization be predicted by profiles of climate for innovation perceptions?” Only part of this question can be answered because normative commitment to the organization (N-I) was excluded from the analyses due to low reliability. However, affective commitment to the organization (A-O) and continuance commitment to the organization (C-O) were analyzed. For none of the LPA models (A, B three-class or B five-class) did latent class membership predict A-O or C-O beyond the latent factor scores.

Research Question 7 asked, “Can affective, normative, and continuance commitment to innovation be predicted by profiles of climate for innovation perceptions?” Although continuance commitment to innovation was not considered due to low reliability, analyses for affective commitment to innovation (A-I) and normative commitment to innovation (N-I) were conducted. Class membership significantly predicted N-I for the MANOVA for the LPA Model A and LPA Model B five-class solutions. In addition, class membership also predicted A-I for the LPA Model B solution beyond the contribution of the ICCS factor scores. It should be noted however, that the effect sizes of these relationship were all low.

Research Question 8 asked, “Can creative and implementation work behaviors be predicted by profiles of climate for innovation perception?” For the MANOVA using the LPA Model A solution, the answer is no: class membership did not predict IWB-C or IWB-I. However, class membership predicted both IWB-C and IWB-I for the LPA Model B five-class solution.

The answers to Research Questions 7 and 8 vary depending on which LPA Model was selected to define class membership. The only result predicted significantly by class membership for LPA Model A and LPA Model B five-class solutions was the prediction of normative commitment to innovation (N-I).

### Homogeneity of Variance Tests

The explicit hypotheses of this study posited that with increasing organizational tenure, the variances associated with climate scores would decrease, or, in other words, ICCS factor scores would become more homogeneous with increasing tenure. Explicit tests of this hypothesis can be conducted at multiple levels of analysis such as the individual level within company, the group/functional group level within company, and at the company level.

**Individual Level within Company.** At the individual level, Levene's Test of Equality of Error Variances was conducted. For this analysis, a MANOVA was specified for each company independently in which level of organizational tenure predicted the nine ICCS latent factor scores. The results of this analysis are presented in Table 45.

Table 45

Overall MANOVA Test for Organizational Tenure as a Predictor of ICCS Factor Scores

Company	Wilks' $\Lambda$	$F$	Hyp $df$	Error $df$	$p$	$\eta^2$	NCP	Power
Company A	0.887	1.276	36	1414.53	0.128	0.029	113.25	0.972
Company B	0.920	1.105	36	1763.05	0.308	0.021	86.09	0.941
Company C	0.846	1.346	36	1062.27	0.085	0.041	117.95	0.979
Company D – Time 1	0.879	1.056	36	1084.75	0.380	0.032	90.77	0.924
Company D – Time 2	0.888	1.223	36	1365.81	0.172	0.029	98.58	0.964

Note: For Company A,  $N = 390$ , for Company B  $N = 483$ , for Company C  $N = 296$ , for Company D Time 1  $N = 302$ , for Company D Time 2  $N = 377$ .

Levene's test compares the residuals associated with prediction of the dependent variables, testing the null hypothesis that error variances are equal across groups. If the null hypothesis is rejected, the pattern of variances among the levels of organizational tenure could be examined for evidence of decreasing variance with

increasing tenure. In accordance with the results of the LPA analyses, for none of the samples was tenure a significant predictor of the nine ICCS scores. The results of Levene's test are presented in Table 46.

Of the 45 company-factor score comparisons, and calculations of Levene's test, only two (4.4%) were statistically significant. For Company C – F4 Agile Decision Making,  $F(4, 291) = 2.410, p < .05$ ; and for Company D (Time 2) – F9 Learning Organization,  $F(4, 372) = 2.488, p < .05$ . Overall, the results of Levene's tests suggests that for each of the five company samples, at the individual level the error variances associated with the prediction of the nine latent ICCS scores from tenure are homogeneous. In other words, at the individual level of analysis, the alternate hypothesis that perceptions of climate become more homogeneous with increased tenure is not supported.

**Group/Functional Unit Level within Company.** At the group level, correlational analyses were performed to test the homogeneity of variance hypothesis. Because tenure data were collected in categorical form, these data were transformed so that each person was assigned the midpoint of their tenure range. I made an exception for the highest tenure group (16 or more years). For this group, I assigned 20 years as the tenure value. The transformation from tenure categories to tenure scores is presented in Table 47.

Group membership was defined as members of the same functional unit within the same company. All cases with missing data on any of the variables were deleted, which resulted in Company A being excluded from this analysis because no functional unit membership data were available. Only groups with five or more cases were included in this analysis. A total of 34 functional unit groups from Companies B, C, and D were identified that met the criteria for inclusion. For the correlational analyses, the mean tenure of each group was correlated with the variance of the nine ICCS latent factor scores for that group. Negative correlations were interpreted as evidence in favor of the hypothesis that with increasing tenure, variance of perceptions of climate decreases. The correlations obtained at the group level for the correlation analysis of tenure with the nine ICCS factor scores are presented in Table 48.

Of the nine comparisons of factor score variance with average tenure, only one was significant,  $r = .435, p < .05$ ; however, this relationship was in the wrong direction. At the group level, the hypothesis of increased homogeneity of variance with increased tenure is not supported.

Table 46

Levene's Test of Equality of Error Variances for Tenure and Innovation-Capacity Climate Survey (ICCS) Factor Scores

Company	ICCS Factor Score	<i>F</i>	<i>ndf</i>	<i>ddf</i>	<i>p</i>
Company A	F1 - Meaningful Work	1.259	4	385	0.286
	F2 – Risk Taking	1.6	4	385	0.174
	F3 - Customer Orientation	0.897	4	385	0.466
	F4 - Agile Decision Making	0.592	4	385	0.668
	F5 - Business Intelligence	0.462	4	385	0.764
	F6 - Open Communication	1.498	4	385	0.202
	F7 - Empowerment	1.086	4	385	0.363
	F8 - Business Planning	0.705	4	385	0.589
	F9 - Learning Organization	0.586	4	385	0.673
Company B	F1 - Meaningful Work	1.526	4	478	0.193
	F2 – Risk Taking	1.207	4	478	0.307
	F3 - Customer Orientation	0.707	4	478	0.588
	F4 - Agile Decision Making	1.974	4	478	0.097
	F5 - Business Intelligence	0.825	4	478	0.51
	F6 - Open Communication	1.53	4	478	0.192
	F7 - Empowerment	1.632	4	478	0.165
	F8 - Business Planning	0.553	4	478	0.697
	F9 - Learning Organization	0.578	4	478	0.679
Company C	F1 - Meaningful Work	1.12	4	291	0.347
	F2 – Risk Taking	2.047	4	291	0.088
	F3 - Customer Orientation	0.484	4	291	0.747
	F4 - Agile Decision Making	2.41	4	291	0.049
	F5 - Business Intelligence	0.784	4	291	0.537
	F6 - Open Communication	1.927	4	291	0.106

Table 46 Continued

	F7 - Empowerment	1.306	4	291	0.268
	F8 - Business Planning	1.87	4	291	0.116
	F9 - Learning Organization	0.94	4	291	0.441
Company D - Time 1	F1 - Meaningful Work	0.641	4	297	0.633
	F2 – Risk Taking	0.941	4	297	0.441
	F3 - Customer Orientation	0.246	4	297	0.912
	F4 - Agile Decision Making	1.554	4	297	0.187
	F5 - Business Intelligence	1.555	4	297	0.186
	F6 - Open Communication	1.131	4	297	0.342
	F7 - Empowerment	1.598	4	297	0.175
	F8 - Business Planning	1.716	4	297	0.146
	F9 - Learning Organization	1.881	4	297	0.114
Company D - Time 2	F1 - Meaningful Work	1.225	4	372	0.300
	F2 – Risk Taking	1.441	4	372	0.220
	F3 - Customer Orientation	1.118	4	372	0.348
	F4 - Agile Decision Making	1.249	4	372	0.290
	F5 - Business Intelligence	1.383	4	372	0.239
	F6 - Open Communication	0.421	4	372	0.794
	F7 - Empowerment	0.332	4	372	0.856
	F8 - Business Planning	1.204	4	372	0.309
	F9 - Learning Organization	2.488	4	372	0.043

Note: Company A ( $N = 390$ ), for B ( $N = 483$ ), for C ( $N = 296$ ), for D-T1 ( $N = 302$ ), for D-T2 ( $N = 377$ ).



Table 47

## Transformation of Tenure from Categorical to Ratio Level Data

Original Tenure Category	New Tenure Value
Less than 1 Year	.5 Years
1 – 5 Years	3 Years
6 – 10 Years	8 Years
11 – 15 Years	13 Years
16 or More Years	20 Years

Note: Midpoint of range was used as an estimate for organizational tenure for all categories except the highest tenure category (16 or more years).

Table 48

## Correlations of Mean Tenure with Innovation-Capacity Climate Survey (ICCS) Latent Factor Variances for Functional Unit Groups

Correlation Analysis	Factor Label	<i>r</i>	<i>p</i>
Mean Tenure with Variance of FS1	Meaningful Work	0.177	0.316
Mean Tenure with Variance of FS2	Risk Taking	0.194	0.271
Mean Tenure with Variance of FS3	Customer Orientation	0.180	0.309
Mean Tenure with Variance of FS4	Agile Decision Making	0.192	0.275
Mean Tenure with Variance of FS5	Business Intelligence	0.105	0.555
Mean Tenure with Variance of FS6	Open Communication	-0.108	0.545
Mean Tenure with Variance of FS7	Empowerment	-0.095	0.594
Mean Tenure with Variance of FS8	Business Planning	0.193	0.275
Mean Tenure with Variance of FS9	Learning Organization	0.435	0.010

Note: *N* = 34. Samples were defined by functional units within companies with more than 5 cases.

**Company Level.** Schneider's original homogeneity of variance hypothesis was made at the organizational level, rather than the group or individual level. Although only five company samples are available for such a comparison, the correlational method described at the group level was also conducted at the company level without regard to functional unit membership. The correlations obtained at the company level for the correlation analysis of tenure with the nine ICCS factor scores are presented in Table 49.

Table 49

Correlations of Mean Tenure with Innovation-Capacity Climate Survey (ICCS) Latent Factor Variances for Companies

Correlation Analysis	Factor Label	<i>R</i>	<i>p</i>
Mean Tenure with Variance of FS1	Meaningful Work	0.071	0.909
Mean Tenure with Variance of FS2	Risk Taking	-0.070	0.911
Mean Tenure with Variance of FS3	Customer Orientation	-0.302	0.622
Mean Tenure with Variance of FS4	Agile Decision Making	-0.627	0.258
Mean Tenure with Variance of FS5	Business Intelligence	-0.678	0.208
Mean Tenure with Variance of FS6	Open Communication	-0.194	0.754
Mean Tenure with Variance of FS7	Empowerment	-0.181	0.771
Mean Tenure with Variance of FS8	Business Planning	-0.366	0.545
Mean Tenure with Variance of FS9	Learning Organization	-0.479	0.414

Note: *N* = 5. Samples were defined by company membership.

Although none of the nine correlations between ICCS factor score variance and mean tenure were statistically significant, the correlations range from  $r = .07$  to  $r = -.678$ , *n.s.* The highest correlations were found for Agile Decision Making ( $r = -.678$ , *n.s.*), Business Intelligence ( $r = -.627$ , *n.s.*), and Learning Organization ( $r = -.479$ , *n.s.*). All estimates of correlation were approximately zero or negative, which provides some support for the homogeneity of variance hypothesis at the company level. If the effect sizes indicated by Pearson's correlation coefficients were found in a larger sample of companies, statistical significance might be found at

the company level. Despite these caveats regarding effect size and sample size in support of the homogeneity of variance hypothesis, statistically it is not supported by the available data.

**Implications of Homogeneity of Variance Tests for the Research Hypotheses.** Research Hypothesis 1 stated, “Within company groups that are defined by functional unit membership, the variability of climate for innovation perceptions will be negatively related to organizational tenure.” This hypothesis was tested using a correlational approach and was soundly rejected by the results. A significant correlation was found for only one dimension of the climate for innovation survey, Learning Organization, and it was in the wrong direction. This finding suggests that for company groups defined by shared functional unit membership, the variability of climate for innovation remains stable or increases with organizational tenure.

Research Hypothesis 2 stated, “Within an individual company, the variability of climate for innovation perceptions will be negatively related to organizational tenure.” This hypothesis is also rejected by the results of Levene’s test and the correlational analysis at the company level. However, the results of the correlational study to examine this relationship used a very small sample size and did yield good effect sizes for several of the ICCS dimensions.

### **Discussion**

Throughout the conduct of this study, I primarily sought to explore the climate for innovation construct as a representation of situational and individual difference influences on people’s perceptions. In this section, I first review the contributions of the present study in terms of instrument development, method development, and the insights gained from investigating its eight research questions. I then discuss the research methods’ limitations. Next, I discuss some potential directions for future research directly from the findings of this study that are consistent with the theoretical and methodological frameworks within which it was designed.

#### **Contributions of the Present Study**

The first major contribution of this research is the introduction into the psychological literature of new scales and adaptations of existing scales, including the ICCS, ANC-O, ANC-I, IWB-C, and IWB-I. Inclusion of these instruments enhances the climate literature, specifically the literature on climate dimensionality, criterion-referencing of climate measures (i.e., the climate for innovation), and the outcomes of climate research.

The ICCS measure of climate for innovation, the first of these new instruments, is a criterion-referenced climate survey as recommended in the climate literature (e.g., Schneider & Reichers, 1983; Jones & James, 1979; Joyce & Slocum, 1984). It is derived from a theoretical model that presents nine correlated factors of the climate for innovation: perceptions of meaningful work, risk taking, agile decision making, customer orientation, business intelligence, open communication, empowerment, business planning, and learning organization. Although the dimensions of the ICCS are related to many other climate measures, two of the dimensions it assesses, business planning and business intelligence, are not commonly surveyed. In this study, the measurement model of the ICCS was confirmed for two samples of data. Indicators of CFA fit suggested that the model was sufficient without modification, and the ICCS factors demonstrated acceptable maximal and internal consistency reliabilities for each subscale and moderate factor intercorrelations consistent with expectations.

In addition to the ICCS, adaptations of the ANC commitment model were introduced to two targets: the organization and innovation. The development of these criterion-referenced adaptations of the ANC scales stemmed from the recommendations of Meyer et al. (2007). Four of the commitment constructs (A-O, C-O, A-I, and N-I) were adequately measured, were shown to fit the data acceptably, and were moderately intercorrelated consistent with expectations. The targeting of ANC commitment to innovation represents an extension of the study by Meyer et al. (2007) of ANC commitment to an organizational change initiative. These researchers found that individuals scoring high in commitment to an organizational change initiative were also more likely to demonstrate behavior supportive of that change initiative, and therefore recommended criterion-referencing of ANC commitments for continued study of such relationships.

Although the criterion-referenced commitment scales in the present study were not compared to other outcome variables, I found that individuals who differed in their perceptions of the climate for innovation also differed in their A-I and N-I commitment. In addition, the mean A-O and C-O scores did not vary greatly with class membership but mean A-I and N-I commitment did. Because normative commitment is generally described as an employee's feeling of obligation, this outcome provides supportive, though indirect, evidence for the influence of individual differences over situational influences in the formation of perceptions of the

climate for innovation. Despite the fact that the measurement models for the N-O and C-I factors failed to achieve sufficient reliability for research standards, I encourage the continued use and development of these constructs. It is worth noting that the subscales of the commitment measures that demonstrated problematic measurement contained reverse-coded items. Development of subscales to measure the N-O and C-I commitment constructs without reverse-coded items may yield higher reliability and internal consistency findings.

An adaptation of scales to measure IWB was also introduced. The IWB-C and IWB-I were intended to measure creative and implementation behaviors, respectively. The measurement models for these scales demonstrated acceptable fit, reliability, and factor intercorrelations for their use in practice. However, the two-factor model of innovative work behavior used in this study seems overly simple. Dorenbosch, van Engen, and Verhagen (2005) hypothesized that it might be more appropriate to assess four factors of innovative work behavior, including 1) problem recognition, 2) idea generation, 3) idea promotion, 4) and idea realization (implementation). Although these researchers did not successfully measure a four-factor IWB model, the more complex model they proposed is appealing because it seems to capture the entirety of the general process of innovation. (Notably, the two-factor model used in this study seems to provide a reliable starting point for developing a more complex measurement model.)

Although innovative work behavior is often conceptualized as the development or implementation of products, processes, objects, or services offered by a company to external agents, some disagree. Kanter's (1983) argument that innovation can and does occur within all parts of an organization and on the part of people at all levels of an organization, for example, is nonetheless consistent with thinking about climates for innovation and commitment to innovation. The items and factors measured by the two-factor IWB scale, which are general, are applicable within all parts of an organization and at all hierarchical levels. The hypothesized four-factor model of IWB, however, may enhance that applicability. Some workers may be unable to generate or implement ideas at work but in communication with others there or even elsewhere they may engage in behaviors associated with recognizing problems in need of innovative solutions and promoting innovations that

would solve them. For all of these reasons, continued development and use of the innovative work behavior scales in both research and practice contexts is recommended.

The second major contribution of the present study is the application of LPA to identify homogeneous groups of individuals who share a perception of the climate for innovation. RQ1 asked about the profile forms for clusters of people with such a shared perception. Although definitive profile forms for classifying climates for innovation did not emerge from this research, important findings did surface. For example, several different and plausible solutions were compared and used in predictive analyses. The form of the profiles for different class solutions was also changed by including demographic covariates to identify class membership, as well as by including distinct subsets of data. Because these two actions were undertaken simultaneously, it is difficult to state the implications of these results with certainty. A number of possibilities are worth mentioning, however.

It is clear that for LPA Model A, which included the covariate data and the excluded the subsample from Company A, fewer classes were identified; the profiles for these classes were significantly different across all ICCS scores; and the fit statistics provided clear guidance that the two-class profile solution was the best solution. In comparison, for LPA Model B, which excluded covariate data but included the subsample from Company A, more classes were identified; the profiles for these classes were not significantly different across all ICCS scores; and the fit statistics did not provide clear guidance for selecting the best class solution. The inclusion of the covariates in the analysis of Model A may have simplified the identification of the class solution. In particular, the significant covariates may have provided the data needed to make clear distinctions between the two classes identified in terms of their ICCS scores, their position on the covariates, and the interactions among these variables. Likewise, the inclusion of the data from Company A in LPA Model B may have introduced some *messiness* to the data that complicated the identification of the best class solution by introducing uncertainty, in the form of unclear or new profiles, into the mix.

The main descriptive finding among the LPA solutions was that mean profiles tended to be relatively flat and particularly so for solutions with a lower number of profiles. By this, I mean that the profiles did not cross, and classes were best described relative to average so that each class maintained its relative position across all ICCS factors. Profile patterns, and therefore classes, were labeled accordingly (e.g., above average,

average, below average). There were, however, points of distinction among the profiles. For example, the open communication factor and the empowerment factor differentiated all of the profiles more than the other ICCS factors did. For every profile solution, a class was identified in which the scores on those specific factors came in well below average. Other factors that tended to differentiate the classes included meaningful work, risk taking, and agile decision making. The remaining factors of customer orientation, business intelligence, business planning, and learning organization seemed, overall, to represent points of convergence rather than divergence for all class solutions. Interestingly, these four factors may also be the ones most likely to be affected by situational influences. This potential is most apparent for business planning and business intelligence, for which situational influences were demonstrated statistically. I also observed that profiles were more clearly differentiated for solutions with fewer latent classes. For solutions with more latent classes, all of the classes were not statistically independent of at least one of the ICCS factors. Despite the differences among the LPA solutions, the general finding was similarity among them. There was also general consistency in terms of the characteristics of the mean profiles. In addition, redundancy was found in the classification of individuals to similar classes across solutions.

The use of LPA to group individuals based on climate for innovation perceptions contributes to the climate literature, specifically on the subtopics of climate focus and climate levels of analysis. Climate for innovation, an individual-level perception, is influenced by both situational and individual differences, possibly in dynamic interaction (Terborg, 1981) or in congruence (Judge & Kristof-Brown, 2004). Dynamic and congruence types of interactions both imply that people and their environments cannot be understood in isolation from each other: their development is complex, dynamic, and interdependent over time. Simple variable approaches are insufficient to represent this complexity. Therefore, I took the position that individual scores should not be aggregated on the basis of membership in a social or organizational group, but rather that aggregation should be based on shared perceptions that theoretically represent the interaction of person and environment. This conceptualization is theoretically consistent with ideas about complexity, with ASA theory (Schneider, 1987), with person-in-environment psychology (Wapner & Demick, 2000), and with interactional psychology (Terborg, 1981; Judge & Kristof-Brown, 2004).

The next set of research questions related to the contributions of the demographic covariates. RQ2 asked which covariates contributed to the latent profile solution. RQ3 and RQ 4 were respectively posed to probe the contribution of situational and individual differences to the latent class solution. RQ5 asked whether situational or individual difference variables were a dominant influence on class membership. For LPA Model A only two demographic covariates, company membership (situation) and organizational level (individual difference) were found to contribute to the class solution in the analysis for which covariates were included. Although the relative contribution of these covariates to the class solution was estimated, the specific nature of that relationship to the class solution was unclear. Additional analyses that compared the demographic covariates to the ICCS scores were conducted to address this shortcoming. For LPA Model B, a post-hoc logistic regression analysis demonstrated that company membership, organizational role, and functional unit membership significantly predicted class membership. However, because of the dissimilar nature of the two samples used for the LPA with covariate and post-hoc logistic regression analyses, MANOVA techniques to predict ICCS scores directly from demographic covariates were also employed.

I used MANOVA to predict the nine ICCS latent factor scores from company membership (situation), functional unit (individual difference), organizational level (individual difference), organizational tenure (individual difference), company by functional unit interaction (situation), company by organizational level interaction (situation), and company by organizational tenure interaction (situation). The MANOVA identified a main effect for functional unit (individual difference), with univariate results indicating that functional unit significantly predicted all ICCS factor scores. In addition, the MANOVA identified a main effect for organizational level (individual difference) with univariate results indicating that organizational level significantly predicted six of the nine ICCS factor scores (meaningful work, risk taking, agile decision making, open communication, empowerment, and business planning). Finally, the MANOVA identified a significant interaction effect for company and organizational level (situation), with univariate results indicating that this interaction significantly predicted business intelligence and business planning. These results were interesting because the two most predictive model effects were individual difference effects, i.e., the main effects of functional unit and organizational role. Based on Holland's (1985) work, it seems reasonable to speculate that



functional unit and organizational role are individual differences because they reflect on occupational membership, which in turn is related to personal attributes such as personality and choice.

The least statistically important but most interesting finding from the MANOVA model is the company by organizational level interaction effect. This interaction term predicted only two of the latent ICCS factor scores (business planning and business intelligence). In retrospect it makes sense that these two ICCS dimensions would be predicted by a situational source and that members of different organizations at different hierarchical levels would have varying amounts of knowledge about business planning and business intelligence. Although business planning and business intelligence are not common constructs in the climate and culture literatures, their inclusion may prove to be useful. First, they both involve describing how employees look beyond the organization's walls to acquire business information and how they use that information internally. These processes are important within the innovation area for the development of ideas and the identification of new ideas to be implemented within the organization. Second, these constructs were the only two predicted by situational variables in this study. This finding suggests that managers should focus on activities that enhance business planning and business intelligence when attempting to influence climate for innovation perceptions.

In answer to RQ2, the only analysis to incorporate the covariates directly was LPA Model A and the results suggested that company (situation) and organizational role (individual difference) contributed to the solution. The nature of those contributions was unclear, however. In answer to RQ3 and RQ4, it appears that both situational factors and individual differences, respectively, were related to the identification of latent classes. In answer to RQ5, my study indicates that individual differences seem to contribute to the development of climate for innovation perceptions more than situational factors do. Although the effect sizes were small, my findings seem to suggest that climate change is better accomplished through selection than through training or organizational policy changes. In short, if a different climate is desired, selecting people with characteristics akin to the desired climate may be the shortest path to realizing climate change.

It should be noted that none of the covariates considered in this study were pure measures of either situation or individual differences, nor did I intend to disentangle their effects completely. My findings suggest

that managerial efforts at climate change should be focused on climate dimensions that are more directly influenced by situational factors (e.g., business planning and business intelligence), and that interventions be planned or enacted with individual differences in mind. The interaction of situation and individual differences should be part of the equation for planned interventions that are aimed to affect organization climate.

The third major contribution of this research study involves the findings related to predicting commitment to the organization (RQ6), commitment to innovation (RQ7), and IWB (RQ8) from class membership. In terms of complexity theory, whether or not latent class (a variable that represents a complex interaction of individual differences and situational influences manifested in climate for innovation perceptions), has an adaptive and emergent property (Geyer, 2003) must be determined. In essence, analyses associated with these findings attempted to discern whether the latent classes represent something more than ICCS factor scores. My main interest was in whether latent class membership is predictive of the commitment and IWBs when climate for innovation perceptions are equal across classes.

I conducted MANCOVA analyses to answer these questions independently for the three class solutions generated. The MANCOVA results were inconsistent and did not provide definitive answers. However, some general findings deserve comment. Among all the dependent variables analyzed, A-O, A-I, N-I, IWB-C, and IWB-I were predicted significantly by at least one of the class solutions beyond the impact of the latent ICCS factor scores. Thus, the class membership did predict commitment and IWB although it did not yield stable predictions over the three different class solutions. The most constant finding was that class membership predicted N-I over two solutions. Because the MANCOVA analyses were complicated by vastly different numbers of individuals assigned to each class for all class solutions, statistical power was low and effect sizes were small. Some of the results were statistically significant but the predictive utility of class membership was decidedly low.

The fourth contribution of this study resulted from testing the hypothesis that the homogeneity of perceptions of climate increases along with increasing organizational tenure, a phenomenon that is implied by the ASA model (Schneider, 1987). Although Schneider and his colleagues posed the homogeneity proposition at the company level, this study tested it at the individual and group levels within company. None of the results

supported the homogeneity hypothesis at a statistically significant level; however, I did find nonsignificant evidence for the homogeneity hypothesis at the company level. At the company level, the effect sizes between homogeneity of variance and organizational tenure were moderate to high even though the small sample size did not yield enough power to find a significant effect. Though a firm conclusion cannot be drawn at this time, the effect size suggests that companies with higher average tenure are more homogenous with respect to the perception of climate, in general, and climate for innovation, in particular. Furthermore, this effect emerged dramatically at the company level.

### **Limitations of the Present Study**

The present research has several shortcomings. First, only the survey method of data collection was used to assess perceptions of climate for innovation, commitment, and IWB. Although this is relatively common practice in climate research, it raises a concern about method bias. It is difficult to imagine a more efficient means to collect perceptions of climate data or ANC commitment data; however, outcome data can and should be collected in a variety of ways. Although differentiating ANC commitment by another means may be challenging, some objective proxy variables for more generalized commitment or organizational citizenship behavior can be identified, such as days missed from work and number of hours worked. For both commitment and IWB, supervisory or peer rating data may be substituted for self-report survey measures. In addition, performance data should not be limited to the individual level, but instead should also be gathered from group outcomes and organizational outcomes. The ultimate goal of climate for innovation research should be to help organizations create climates that support innovation so that desired individual, group, and organizational outcomes related to innovation can be achieved. As described earlier, innovation occurs throughout the organization, in all segments and at all levels. It follows logically that innovation outcomes may also occur at the individual level (e.g., commitment, ideation, making suggestions to improve processes), group level (e.g., successful deployment of new processes, number of patents attained by a group), and company level (e.g., market share, return on investment, profitability of new products or services). In sum, climate for innovation research should assess important outcomes at all levels.

A second shortcoming of the present study concerns the inconsistencies found across LPA results. For instance, the analysis was complicated by the absence of one key demographic variable, functional unit membership, for one company sample (Company A). Consequently, the LPA class solutions were highly variable in terms of the number of cases assigned to each class and the number of classes to which cases could be assigned. Although equal class sizes were not expected *a priori*, neither were vastly different class sizes anticipated. Subsequent analyses using class membership, therefore, were complicated by unequal class sizes. Although some consistency in class membership was clear across the three class solutions considered, that consistency did not continue to the predictive part of this study. And, although class membership was found to be a significant predictor, effect sizes and variance accounted for in these models were very low because of unequal class sizes. Consequently, it is unclear which of the class solutions generated by these procedures is preferable, or even that these are the correct class solutions. With the introduction of additional cases or samples, or the inclusion of different variables or covariates, it seems likely that class solutions will change dramatically.

A third shortcoming in the present study concerns the possible exclusion of useful demographic covariates. The demographic covariates for this study were selected because they are reasonable proxies for individual differences and situational influences that are commonly assessed and available in organizations. Functional unit (individual difference) is a reasonable proxy for occupational choice, which research has shown to be related to personality and interests (Holland, 1985). For instance, salespeople are likely found in sales functions while machine operators are likely to be found in manufacturing functions. Similarly, organizational level (individual difference) is related to occupational choice. Tenure has been shown to be a reasonable proxy for age (Pond & Geyer, 1991). To the extent that the effects associated with function, organizational level, and tenure cross organizational membership, these represent individual difference variables in an acceptable way. However, if company membership moderates the effect of functional unit membership, organizational role or tenure, these variables become indicators of situational differences to the extent that the moderation occurs. Although the present study found that individual differences were more predictive of perceptions of the climate for innovation, the demographic covariates used to measure individual differences were distal not proximal.

Occupation or job role may be a more proximal indicator than functional unit; and, similarly, actual age may be a better predictor than organizational tenure as a proxy for age. In addition, other individual difference covariates could also be included, such as education, sex, geographic region, and many others. Covariates that more specifically indicate situational influences should also be considered. For instance, participation in various training programs, work group membership, industry, worksite location, reporting relationships, company policies or practices, and other situational variables, if included, could provide more direct indications of situation. It would be particularly important to include covariates related to industry, organizational policies, and location in cross-company analyses.

The fourth shortcoming of note is that, although this study included a relatively large sample size from several companies, the companies were similar in that they identified as innovators and as global, high-technology firms. Therefore, it may be reasonable to assume that these companies have restricted variance on climate for innovation perceptions or commitment and innovation outcomes. The sample for the current study did not include small companies, start-up companies, virtual companies, or companies that lack research and development functions such as retailers and government agencies. How the inclusion of such organizations and others would affect the identification of discrete classes, or affect the form of the latent profiles, remains unknown. Nonetheless, I would expect to find increased variability of climate for innovation perceptions, commitment to innovation, and innovative work behavior. Moreover I would expect to identify new latent classes and changes in the distribution of members of previously identified latent classes. Because LPA is a model-based technique, the latent classes it identifies represent latent classes for the population from which samples are drawn. A much larger and more diverse sample would be required in order to identify all latent classes and establish stability in the class solutions.

### **Directions for Future Research**

Many directions for future research are indicated by the discussion of this study's contributions and shortcomings. For instance, continued development of the climate for innovation, commitment, and innovative work behavior scales is needed. In addition, subsequent investigators should replicate and extend the findings of this research by using more diverse samples and additional demographic indicators of situation and individual

differences. They should also apply the techniques described in this paper to other climate for innovation data in order to identify similarities and differences in class solutions. Other variables should be considered in addition to demographic covariates. In the person-environment (P-E) fit literature, for example, measures of personality are often used as indications of individual differences (Judge & Kristof-Brown, 2004). Inclusion of such variables in relation to climate for innovation would be likely to provide insight to researchers interested in personality, climate, and P-E fit. In addition to possible research topics directly identified from the present study, trends in the climate and other psychological literatures suggest new directions with the potential to influence thinking and practice about climate and related areas dramatically. Some of the most promising new directions are discussed below.

That climate research has progressed from generalized climate constructs to the climates for something approach suggests the increased importance of situation or context in the study of climate. In a related trend, focus has shifted slightly from developing predictors to predicting outcomes. The climate literature has also moved from near-exclusive reliance on variable approaches to the incorporation of pattern approaches into variable models. One example, the use of clustering techniques (e.g., Joyce and Slocum, 1984), suggests the increased importance of individuals in the study of climate. Similarly, the focus on main effects has progressed so much that interest has also grown in interactions and dynamic interactions (Terborg, 1981; Judge & Kristof-Brown, 2004) and systems thinking (Wapner & Demick, 2000; Geyer, 2003).

I see two major implications in these trends for future research. One is that the variables and relationships among variables in climate research should be conceptualized in terms of dynamic interactions between person and situation. The other is that methodological development is required in order to represent the full complexity of person and situation interactions or systems. The remainder of this section discusses the second implication explicitly, but relates to the first as well.

Methodological development in climate research will undoubtedly involve modeling approaches. Therefore, future research should include person and situation variables, and models should be designed to assess the complex interactions among these variables. Pattern approaches such as clustering techniques are recommended; of these, LPA is particularly promising for reasons listed previously (e.g., it can be used to

account for individual variation in climate perceptions unaccounted for by variable approaches). In the present study, class membership was conceptualized as representing a combined effect of situational and individual difference variables. In effect, class membership became a complex and dynamic variable used to predict outcomes. However, other applications of LPA may improve this technique.

The use of latent factor scores by the LPA conducted in this study had the effect of holding the covariance among the factors constant for all classes and assuring that classes were compared on the basis of mean differences alone. An alternative method, and an interesting one, would be to conduct an LPA on items rather than on latent factor scores. Then CFA techniques could be used to test for the equality of the covariance matrices among the resultant latent classes to determine whether the model varies between classes. In effect, a different model could be fit to each class. Although it could be argued that comparing people across different models is less informative, or that finding a nonconstant factor structure is indicative of poor measurement, these would not necessarily be so. Rather, a nonconstant factor structure could significantly extend the literature by sharpening the focus on people and their perceptions of the climate for innovation. It may be that people conceive of climate for innovation qualitatively differently, which would be represented by competing factor structures for different classes. Such a method would still involve both pattern and variable approaches but would increase emphasis on the pattern approach by not assuming that climate for innovation factors are constant across classes of individuals.

The present study used class variables to predict outcomes. However, it may be that position on the outcome variables should be specified as input, or as a discriminating variable for the class solution, rather than as outcomes of a class solution. In other words, latent classes may be identified based on the dynamic and complex interactions among climate perceptions, demographic covariates, *and* outcomes. This supposition, if true, might explain the low effect sizes in the present study. Maybe outcome variables, such as commitment or innovative work behavior, discriminate classes. Similarly, it may be that profiles on performance are more useful in predicting climate perceptions than vice versa. Given the trend of focusing on predicting outcomes, organizations' interest in discriminating individuals based on their performance profiles could be increasing. If

so, individual-level class solutions that include performance indicators may be very useful in predicting higher level outcomes, such as those at the work group or organizational levels.

Another possible direction for future research involving model specification using LPA is the assignment of membership to classes. LPA's generation of probabilities of class membership indicates a variety of uses for probability data. For example, when calculating mean factor scores for a latent class, weighting by probability of class membership may significantly change the mean profiles. Such probabilities could also be used to identify *core* versus *noncore* members of a latent class. In addition, probabilities could be used to identify smaller groups with the highest agreement, which would allow for more intensive study of group differences.

Future research efforts should include LPA and other approaches that emphasize people, their perceptions, and their interaction with the environment. Longitudinal designs, such as latent growth modeling, should be incorporated into studies of how individual perceptions of climate change over time. In addition, quantitative methods should be supplemented with qualitative methods such as case studies of individuals and of organizational environments. Methodological diversity will become more and more important if researchers want to focus on people, contexts, and the dynamic interactions among them.

## **Conclusion**

This study focused on the climate for innovation and introduced a measure of this construct to the psychological literature. Although the ICCS measures constructs that are indicative of a climate for innovation, I do not presume that the most innovative company is the one with high, persistent perceptions of the climate, across all dimensions, for everyone in the organization. The right mix is yet to be determined. In accordance with the ASA theory, exposure to a diversity of ideas is important for people in organizations to innovate, to adapt, and to otherwise change. In the context of innovation, it seems clear that agreement is secondary to diversity. A better practice could be to ensure that a diversity of ideas and perspectives is represented on teams, in groups, or in companies, recognizing that this may result in lower agreement. The best climate for innovation may well belong to the company with the most groups of people who hold differing perceptions. Rather than asking, "Does everyone in this group agree?" it might make more sense to ask questions such as, "Which people



agree and why do they do so?” and “Does the agreement and disagreement that exists otherwise align with the organization’s ultimate goal of effectiveness?” In order to be truly innovative, an organization may require making peace with a paradox: that high agreement among employees may actually diminish its innovativeness.

I take the position that the perception of climate is an individual-level, subjective phenomenon that represents a dynamic and complex interaction of individual differences and situational influences. Although my study did not produce conclusive evidence for this view, it does demonstrate an exploratory first step toward a new way to study climate in organizations. I believe that modeling in ways that account for complex interactions between people and environments will improve the prediction of outcomes such as commitment, innovative work behaviors, and many others.

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**Appendices**

**Appendix A: Instruments**

This Appendix contains the instruction and items (with hypothesized factors indicated by subheadings) for four instruments:

1. Innovation-Capacity Climate Survey (ICCS)
2. Perceived Organizational Support (POS) scale
3. Innovative Work Behaviors (IWB) scales
4. Affective, Normative, and Continuance Commitment scales

**Innovation-Capacity Climate Survey (ICCS)**

Please think about your particular work environment and respond honestly to the survey statements.  
For each statement, indicate the degree to which you agree or disagree using the 5-point scale provided.

**Meaningful Work**

1. People know that what they do impacts what happens in the organization.
2. The work we do in the organization is meaningful.
3. People know what they do impacts customers.

**Risk-taking**

4. Being innovative is characteristic of the organization's culture.
5. The organization's culture encourages employees to try new ideas.
6. Being willing to take risks is characteristic of the organization.
7. The organization is adaptable to new situations.
8. Diversity of thought is encouraged in the organization.

**Customer Orientation**

9. In the organization, we regularly look at how we offer customers superior value.
10. In the organization, we regularly re-examine who are the target customers for what we do.
11. In the organization, we regularly look at how we can add more value to our customers.
12. We are encouraged to think in terms of total customer solutions.
13. We are encouraged to think in terms of what adds value to our customers.

**Agile Decision Making**

14. In the organization, we assess opportunities without being constrained by where we are right now.
15. In the organization, decisions are usually made at the level where the best information is available.
16. Everyone is involved to some degree in our organizational planning.

17. We respond quickly to changes in the business environment.

#### Business Intelligence

18. In the organization, we regularly monitor competitors.
19. In the organization, we use competitors as our benchmark.
20. We respond quickly to competitors' actions.

#### Open Communication

21. Employees feel free to challenge the status quo.
22. People feel it's OK to speak out if they disagree with others' decisions.
23. The organization culture encourages members being open to change.

#### Empowerment

24. People are encouraged to identify concerns about work.
25. People are encouraged to address work problems in their own area.
26. Individual independence is respected by the organization.

#### Business Planning

27. In the organization, we use scenario planning as part of our business plan creation.
28. In the organization, we use simulations as part of our business plan creation.
29. We estimate risks in each step when developing a business plan.
30. The organization takes a broad value chain perspective when examining new opportunities.

#### Learning Organization

31. When redesigning products, processes, or services we maximize what employees have learned from their working experiences.
32. One of our innovation practices is finding out how our customers really use our products.
33. One of our innovation strategy development processes is identifying similar ways our customers use our products.

**Innovative Work Behaviors (IWB)**

Please indicate how often you engage in the behaviors listed below using the 5-point scale provided, where 1 = never, and 5 = very frequently.

**Creative Behaviors**

1. I generate ideas to improve products, services, processes, or procedures.
2. I generate new solutions to old problems.
3. I experiment with new ways of working.

**Implementation Behaviors**

4. I work with colleagues to translate ideas into new products, services, processes, or procedures.
5. I eliminate roadblocks in the process of idea implementation.
6. I sell my ideas to my colleagues and supervisor to gain their support.



**Affective, Normative, and Continuance Commitment Scales**

For each statement, please indicate the degree to which you agree or disagree using the 5-point scale provided, where 1 = strongly agree and 5 = strongly disagree.

**Affective Commitment to the Organization**

1. Remaining a member of this organization is important to me.
2. I would be very happy to spend the rest of my career with this organization.
3. I feel a strong sense of belonging to this organization.

**Continuance Commitment to the Organization**

4. It would be costly for me to leave this organization now.
5. Right now, staying with this organization is a matter of necessity.
6. I have invested too much in this organization to consider leaving.

**Normative Commitment to the Organization**

7. I would feel guilty if I left this organization now.
8. I do not feel any moral obligation to this organization.
9. I feel a sense of implicit duty to this organization.

**Affective Commitment to Innovation**

10. Achieving innovation is as important to me as it is to the organization.
11. I really want to be involved in innovative work.
12. Working to help assure the success of innovation objectives is important to me.

**Continuance Commitment to Innovation**

13. It could be costly for me if I do not achieve innovation goals.
14. I have a lot to lose by failing to meet this organization's innovation objectives.
15. It would be risky for me to speak out against this organization's innovation goals.

Normative Commitment to Innovation

16. I owe it to this organization to do my best to achieve its innovation objectives.
17. I feel a real sense of obligation to try to meet innovation goals.
18. I feel it is my implicit duty to work to achieve innovation goals.

**Appendix B: Comparison of the Theoretical Dimensions of the ICCS and Other Measures**

Table 50

Comparison of ICCS Theoretical Dimensions to Other Measures

ICCS	CCQ	KEYS	SSSI	TCI	Other Theoretical Dimensions
Meaningful Work	Challenge	Challenging Work			
Risk Taking	Risk Taking	Organizational Encouragement	Leadership	Support for Innovation	Innovation and Risk-Taking (O'Reilly Chatman & Caldwell, 1991); Openness to Change and Creativity (Jassawalla & Sashittal, 2002); Creative Behaviors (McLean, 2005); Innovativeness and Risk-Taking (Lumpkin & Dess, 1996)
Customer Orientation					Focusing on Customers (Deal & Kennedy, 1982); Proactive Aggressiveness (Lumpkin & Dess, 1996); Outcome Orientation (O'Reilly, Chatman, & Caldwell, 1991); Intersecting Territories (Kanter, 1988)
Decision Making		Organizational Encouragement	Leadership	Participative Safety	Trust (Jassawalla & Sashittal, 2002); Autonomy and Proactiveness (Lumpkin & Dess, 1996); Decentralized Decision-Making (Angle, 1989); Shared Pride/Faith in People's Talents (Kanter, 1988)
Business Intelligence					Competitive Aggressiveness (Lumpkin & Dess, 1996); Aggressiveness (O'Reilly, Chatman, and Caldwell, 1991)

Table 50 Continued.

Open Communication	Debates, Trust/ Openness, Idea Support	Supervisory Encouragement, Work Group Supports	Participative Safety	Open Communication (Angle, 1989); Open Communication (McLean, 2005); Trust (Jassawalla & Sashittal, 2002); Open Communication (Angle, 1989)
Empowerment	Freedom	Freedom	Ownership, Norms for Diversity	Enabling and Motivating (McLean, 2005); Initiative-Taking (Jassawalla & Sashittal, 2002); Autonomy (Lumpkin & Dess, 1996); Proactiveness (Lumpkin & Dess, 1996); Shared Pride/Faith in People's Talents (Kanter, 1988)
Business Planning				Entrepreneurial Orientation (Lumpkin & Dess, 1996)
Learning		Continuous Development		Innovative Role Models (McLean, 2005)

Note. ICCS is Innovation-Capacity Climate Survey (Aiman-Smith, Goodrich, Roberts, and Scinta (2005); CCQ is the Climate for Creativity Questionnaire (Ekvall, 1996); KEYS is the KEYS: Assessing Climate for Creativity Scale (Amabile et al., 1996); SSSI is the Siegel Scale in Support of Innovation (Siegel & Kaemmerer, 1978); TCI is the Team Climate Inventory (Anderson & West, 1996).

**Appendix C: Results for Latent Profile Analysis (LPA) Model A and B Including Outlier Data**

The LPA results presented here follow the same theoretical models and methodological procedures as did analyses presented in the Results section of this document. This Appendix is presented in parallel format to the Results section. The only difference is that the datasets used to generate these results include multivariate outlier data whereas those presented earlier did not. First, the results for LPA Model A (Including Outliers) and LPA Model B (Including Outliers) are presented. At the end of this Appendix, data related to the distribution of outliers across the latent class solutions for LPA Model A (Including Outliers) and LPA Model B (Including Outliers) are presented.

**LPA Model A (Including Outliers).** The removal of cases with data missing on the covariates resulted in a reduced sample size ( $N = 1419$ ). Sample summary statistics by company, functional unit, organizational level, and tenure are presented in Tables 51 – 54, respectively.

In LPA Model A (Including Outliers), nine latent factor scores and four categorical covariates (company, functional unit, organizational level, and tenure) were used to identify latent classes of individuals who share a latent profile on the ICCS. The Mplus analysis type was specified as mixture with an integration algorithm. The ICCS latent factor scores were free to correlate with the constraint that the correlations be held constant across classes. The demographic covariance matrices were set free to differ.

Table 51

Frequency Data for Company Membership for Latent Profile Analysis (LPA) Model A (Including Outliers)  
Sample

Level	<i>f</i>	%
Company B	476	33.5
Company C	292	20.6
Company D – Time 1	290	20.4
Company D – Time 2 (Target Sample)	361	25.4

Note.  $N = 1419$ .

Analysis of LPA Model began with the specification of a two-class model; class size was increased in subsequent iterations until fit declined. The fit statistics generated for four iterations of LPA Model A are presented in Table 55. No additional iterations were conducted.

Table 52

Frequency Data for Functional Unit Membership for Latent Profile Analysis (LPA) Model A Sample

Functional Unit	<i>f</i>	%
Business and General Management / Corporate	56	3.9
Supply Chain (Procurement, Customer Service, Operations Planning)	85	6.0
Manufacturing and Operations	522	36.8
Environmental Health and Safety	35	2.5
Human Resources	59	4.2
Marketing and Sales	288	20.3
Research and Development	183	12.9
Information Technology	58	4.1
Finance/Accounting/Legal	133	9.4

Note. *N* = 1419.

Table 53

Frequency Data for Organizational level for Latent Profile Analysis (LPA) Model A (Including Outliers) Sample

Organizational Level	<i>f</i>	%
Non-manager	685	48.3
Manager	603	42.5
Executive	131	9.2

Note. *N* = 1419.



Table 54

Frequency Data for Organizational Tenure for Latent Profile Analysis (LPA) Model A (Including Outliers)  
Sample

Organizational Tenure	<i>f</i>	%
Less than 1 Year	95	6.7
1 – 5 Years	442	31.1
6 – 10 Years	234	16.5
11 – 15 Years	185	13.0
16 or More Years	463	32.6

Note. *N* = 1419.

Table 55

Latent Profile Analysis (LPA) Model A (Including Outliers) Fit Statistics

Statistics	Number of Classes ( <i>k</i> )			
	2	3	4	5
Akaike Information Criterion (AIC)	38509.70	38314.21	38219.55	38149.17
Bayesian Information Criterion (BIC)	38956.60	38834.72	38813.67	38816.90
Entropy	0.91	0.83	0.84	0.83
Vuong-Lo-Mendell-Rubin Likelihood Ratio (for <i>k</i> versus <i>k</i> - 1 classes) <i>p</i> value	0.02	0.35	0.51	0.29

Note. *N* = 1419.

For each iteration, the AIC value decreased. The BIC decreased for three- and four-class solutions but rose for the five-class solution. Entropy was highest for the two-class solution (.91), dropped for the three-class solution (.83), and remained approximately equal for the four- (.84), and five-class (.83) solutions. The Vuong-Lo-Mendell-Rubin Likelihood Ratio Test generated  $p = 0.000$  for the two-class model, indicating that the two-class solution is significantly better than a single-class model. When comparing the three-class model to the

two-class model, however, the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test generated a nonsignificant  $p$  value = .35. The fit statistics suggest that the two-class solution is the most appropriate for these data.

The overall contributions of the covariates in this model are determined by a  $\chi^2$  test that compares the specified model (in which covariates are free to differ) versus the null model (in which the covariates are constrained to be constant). The test for the significance of the covariates for two-class solution resulted in  $\chi^2(521) = 2198.84$ ,  $p < .000$ , which indicates that model fit is significantly improved by the inclusion of the covariates.

The two-class solution resulted one relatively large class ( $n = 1243$ ) and one relatively small class ( $n = 176$ ). Although this information does not indicate the appropriateness of model fit, it is important to examine the average probability of class assignment in order to determine the appropriateness of fit. The probability of assignment to latent classes was also examined to determine the quality of the two-class solution. The probability of assignment data are presented in Table 56 with the number and proportion of individuals assigned to each latent class. The average probability for latent class membership was found to be high, ranging from  $p = .91$  to  $p = .98$ , while the probability of being assigned to a different latent class was  $p = .09$ , ranging from  $p = 0.00$  to  $p = 0.06$  for all classes. This evidence supports the two-class solution.

Table 56

Average Latent Class Probabilities for Latent Class Membership (Row) by Most Likely Latent Class (Column) for Latent Class Analysis Model A (Outliers Included) Two-Class Solution

Class	<i>N</i>	%	Most Likely Latent Class	
			1	2
1	1243	86.7	.98	
2	176	13.3	0.07	0.93

Note.  $N = 1419$ .

The latent ICCS factors were allowed to co-vary using the mixture modeling technique, but those correlations were held constant across the classes. The latent factor correlation matrix estimated by Mplus in generating the class solution is presented in Table 57. The factor intercorrelations among the ICCS latent factors were all moderate, ranging from  $r = .20$  to  $.64$ , and significant at  $p < .0001$ .

Table 57

Innovation-Capacity Climate Survey (ICCS) Factor Intercorrelations Resulting from Latent Profile Analysis Model A (Outliers Included) Two-Class Solution

Latent Factor	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1. Meaningful Work	1.00								
F2. Risk Taking	0.46	1.00							
F3. Customer Orientation	0.47	0.51	1.00						
F4. Agile Decision Making	0.47	0.64	0.51	1.00					
F5. Business Intelligence	0.26	0.35	0.49	0.43	1.00				
F6. Open Communication	0.35	0.54	0.32	0.52	0.23	1.00			
F7. Empowerment	0.31	0.37	0.28	0.36	0.20	0.43	1.00		
F8. Business Planning	0.25	0.38	0.43	0.46	0.53	0.28	0.23	1.00	
F9. Learning Organization	0.34	0.44	0.57	0.48	0.50	0.30	0.25	0.51	1.00

Note.  $N = 1419$ . \*All correlations significant at  $p < .0001$ .

The final consideration for the appropriateness of model fit is the interpretability of the latent profiles. Each latent profile was graphed by plotting the mean factor score on each latent factor by latent class membership. The means for each class are presented in Table 58, and a depiction of latent factor score profiles is presented in Figure 12. The two latent profiles are clearly distinct in terms of means factor scores and profile shape. The first latent class ( $n = 1243$ ) has a relatively flat profile that sits just above average for all of the ICCS latent factor scores. The second latent class ( $n = 176$ ) sits below average for all ICCS latent factor scores.

Although the profile for the second latent class is also relatively flat, two scores for the second latent class are dramatically lower, including the scores for Open Communication (F6) Empowerment (F7).

The contribution of the individual demographic covariates was investigated next. Estimates, standard errors, significance values, and logistic regression odds ratio results for each covariate entered into LPA Model A are presented in Table 59. It was found that organizational level was significantly related to the latent class solution while company membership, functional unit and organizational tenure were unrelated.

Table 58

Summary Statistics for Latent Profile Analysis Model A (Including Outliers) Classes on Innovation-Capacity Climate Survey (ICCS) Factor Scores

Latent Factor	Latent Profile Analysis Model A (Including Outliers) Class Solution			
	1 ( <i>n</i> = 1243)		2 ( <i>n</i> = 176)	
	<i>M</i>	SE	<i>M</i>	SE
F1. Meaningful Work	0.20	0.02	-0.79	0.10
F2. Risk Taking	0.22	0.03	-0.96	0.10
F3. Customer Orientation	0.12	0.03	-0.74	0.10
F4. Agile Decision Making	0.23	0.03	-0.87	0.08
F5. Business Intelligence	0.07	0.03	-0.45	0.08
F6. Open Communication	0.26	0.03	-1.22	0.08
F7. Empowerment	0.33	0.02	-1.71	0.08
F8. Business Planning	0.12	0.03	-0.42	0.09
F9. Learning Organization	0.09	0.03	-0.52	0.09

Note. Latent factor is the ICCS latent variable.

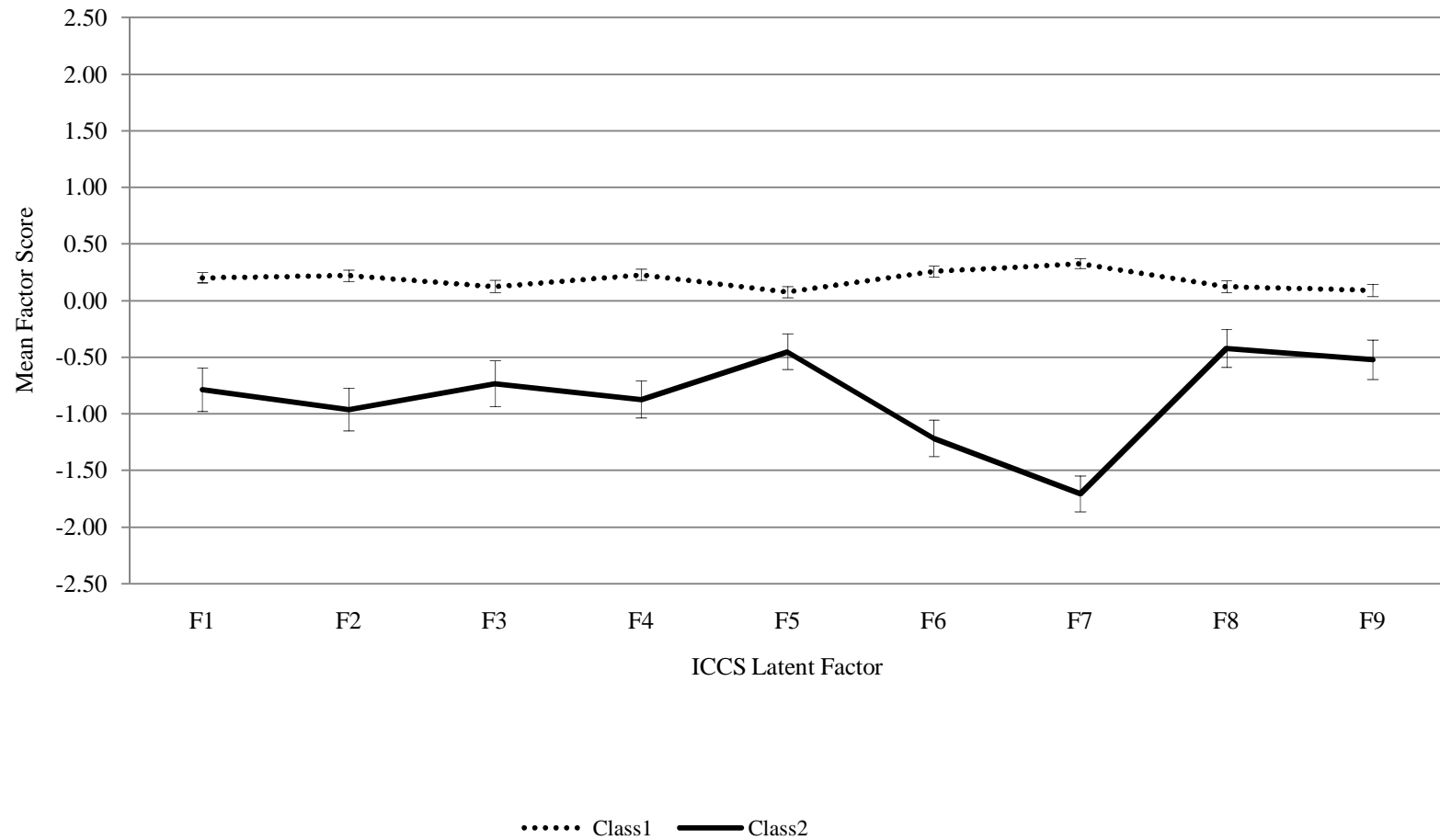


Figure 12. Latent Profiles for LPA Model A (Outliers Included) Two-Class Innovation-Capacity Climate Survey (ICCS).

F1 is Meaningful Work, F2 is Risk Taking, F3 is Customer Orientation, F4 is Agile Decision Making, F5 is Business Intelligence, F6 is Open Communication, F7 is Empowerment, F8 is Business Planning, and F9 is Learning Organization.

Table 59

Demographic Covariate Tests of Significance for Latent Profile Analysis (LPA) Model A (Outliers Included), Two-Class Solution

Statistics	Number of Classes ( <i>k</i> )			
	$\beta$	<i>SE</i>	Odds Ratio	<i>p</i>
Company	.13	.13	1.43	.13
Functional Unit	.05	.5	1.05	.26
Organizational Level	.664	.19	1.94	.00
Organizational Tenure	.02	.07	1.01	.77

Note. *N* = 1419. All covariates included in model.

Based on all of the information available, it was concluded that the two-class solution for LPA Model A (Including Outliers) appropriately fits the data. The statistical indices of fit suggest that the two-factor class is the best-fitting model, the classification probabilities are acceptably high, factor intercorrelations are moderate, and the profiles are interpretable. Only one covariate, organizational level, was significantly related to the solution. For lack of more information to describe these two latent classes, the first (*n* = 1243) is tentatively labeled “Above Average” and the second (*n* = 176) is tentatively labeled “Below Average.” LPA Model B (Including Outliers) attempts to replicate these findings using a different technique. The results for LPA Model B (Including Outliers) are presented in the next section.

**LPA Model B (Including Outliers).** In LPA Model B nine latent factor scores were used to identify latent classes of individuals who share a latent profile on the ICCS. The Mplus analysis type was specified as mixture. The ICCS latent factor scores were free to correlate with the constraint that the correlations be held constant across classes. LPA Model B did not require cases to be eliminated due to missing demographic covariate data. As a result, the data from all companies could be used in this analysis and the sample size is larger (*N* = 1891). The sample demographics remain unchanged from the CFA stage of analysis.

The LPA iteration procedures described above were replicated on the new dataset ( $N = 1891$ ) in the attempt to generate a class solution that adequately fits the data in the absence of demographic covariate influence. The indicators of fit for LPA Model B are presented in Table 60.

Table 60

Latent Profile Analysis (LPA) results LPA Model B (Including Outliers)

Statistics	Number of Classes ( $k$ )				
	2	3	4	5	6
Akaike Information Criterion (AIC)	30141.78	29972.95	29808.81	29692.94	29648.21
Bayesian Information Criterion (BIC),	30496.65	30383.27	30274.58	30214.16	30224.87
Entropy	0.89	0.80	0.90	0.83	0.81
Vuong-Lo-Mendell-Rubin Likelihood Ratio (for $k$ versus $k - 1$ classes) $p$ value	0.00	0.00	0.00	0.00	0.16

Note.  $N = 1891$ .

For each iteration of the model the AIC value decreased. The BIC decreased until the six-class model was specified. At this point, the BIC increased from 30274.58 to 30224.87. Entropy values that approach 1.0 are considered an indication of good model fit. Entropy increased for the first three iterations of the model, reaching a high of .90 for the four-class solution. It dropped .82 for the five-class model and remained approximately steady for the six-class model. The explicit test of model fit is the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test, which compares the model to  $k$  classes to the model with  $(k - 1)$  classes. When the  $p > .05$ , the model with  $k$  classes is rejected and the model with  $(k - 1)$  classes is judged to fit. The Vuong-Lo-Mendell-Rubin Likelihood Ratio Test generated  $p$  values of 0.00 for the two-, three-, four-, and five-class solutions. However, for the six-class solution,  $p = 0.16$ . The AIC and entropy statistics provide evidence of improving fit with each iteration of the model. The BIC and Vuong-Lo-Mendell-Rubin Likelihood Ratio tests provide clear evidence that the five-class solution is the best fit to the data. No additional iterations of the data were performed.

The number of individuals in each class varies from almost 60 percent of the sample assigned to the largest class to only three percent of the sample assigned to the smallest class. The probability of assignment to latent classes was also examined to determine the quality of the five-class solution. The probability of assignment data is presented in Table 61 with the number and proportion of individuals assigned to each latent class. The average probability for latent class membership was found to be high, ranging from .83 to .93, while the average probability of being assigned to a different latent class was found to be near zero, ranging from 0.00 to 0.06 for all classes. This evidence supports the five-class solution.

Table 61

Average Latent Class Probabilities for Latent Class Membership (Row) by Most Likely Latent Class (Column) for ICCS Five-Class Solution Without Covariates

Class	N	Proportion	Most Likely Latent Class				
			1	2	3	4	5
1	188	.10	0.87				
2	106	.06	0.00	0.85			
3	66	.03	0.06	0.04	0.87		
4	410	.22	0.04	0.02	0.00	0.83	
5	1121	.59	0.01	0.01	0.00	0.06	0.93

Note.  $N = 1891$ .

The latent ICCS factors were allowed to co-vary using the mixture modeling technique, but those correlations were held constant across the classes. The latent factor correlation matrix estimated by Mplus in generating the class solution is presented in Table 62. The factor intercorrelations among the ICCS latent factors were modest, ranging from  $r = .12$  to  $.44$ .

The final consideration for the appropriateness of model fit is the interpretability of the latent profiles. Each latent profile was graphed by plotting the mean factor score on each latent factor by latent class



membership. The depiction of latent factor score profiles is presented in Figure 13. The estimated means for each class are presented in Table 63.

Table 62

Innovation-Capacity Climate Survey (ICCS) Factor Intercorrelations Latent Profile Analysis Five-Class Solution

Latent Factor	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1. Meaningful Work	1.00								
F2. Risk Taking	0.26	1.00							
F3. Customer Orientation	0.29	0.37	1.00						
F4. Agile Decision Making	0.27	0.44	0.37	1.00					
F5. Business Intelligence	0.16	0.25	0.40	0.33	1.00				
F6. Open Communication	0.15	0.30	0.17	0.28	0.12	1.00			
F7. Empowerment	0.19	0.25	0.19	0.24	0.13	0.24	1.00		
F8. Business Planning	0.14	0.28	0.35	0.36	0.47	0.15	0.15	1.00	
F9. Learning Organization	0.20	0.30	0.45	0.34	0.42	0.14	0.15	0.42	1.00

Note.  $N = 1891$ . \*All correlations significant at  $p < .0001$ .

Some of the latent profiles are clearly distinct, for instance, the profile for Latent Class 2, Latent Class 3, and Latent Class 5 display patterns that are clearly differentiated from all other profiles. Although Latent Class 1 and Latent Class 4 differ from the other profiles, both sit just below average on all variables and share a similar shape with one exception: they differ on Factor 7, Empowerment, with Latent Class 1 demonstrating a lower score on this factor. Based on all of the information available, it was concluded that the five-class LPA solution is appropriate. The statistical indices of fit suggest that the five-factor class is the best-fitting model, the classification probabilities are acceptably high, factor intercorrelations are moderate or low, and the profiles are interpretable.

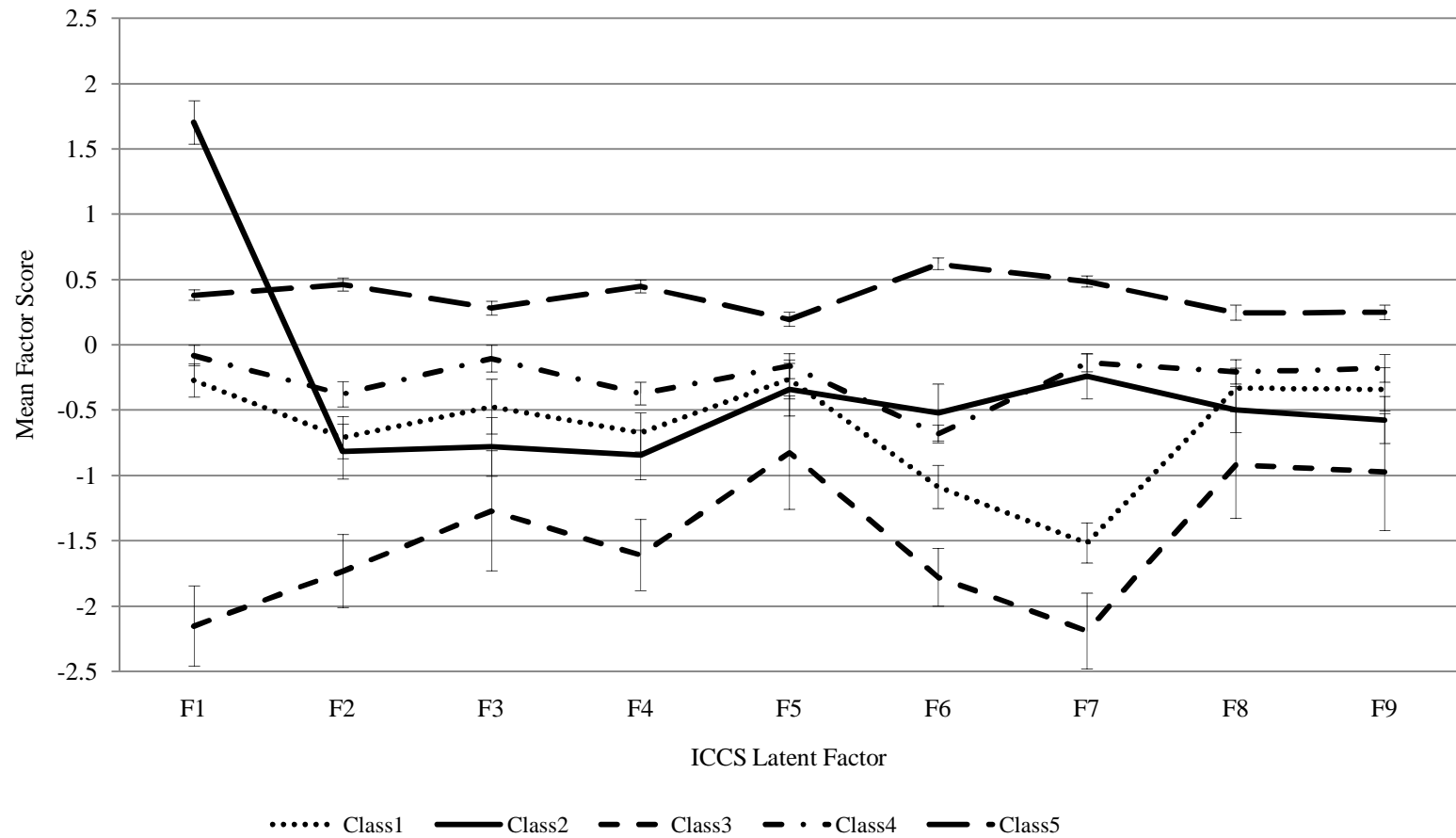


Figure 13. Latent Profiles for Five-Class Innovation-Capacity Climate Survey (ICCS).

F1 is Meaningful Work, F2 is Risk Taking, F3 is Customer Orientation, F4 is Agile Decision Making, F5 is Business Intelligence, F6 is Open Communication, F7 is Empowerment, F8 is Business Planning, and F9 is Learning Organization.

Table 63

Summary Statistics for Latent Profile Analysis Model B (Including Outliers) Five-Class Solution on Innovation-Capacity Climate Survey (ICCS) Factor Scores

Latent Factor	Latent Profile Analysis Model B (Including Outlier) Class Solution									
	1 ( <i>n</i> = 188)		2 ( <i>n</i> = 106)		3 ( <i>n</i> = 66)		4 ( <i>n</i> = 410)		5 ( <i>n</i> = 1121)	
	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>
F1. Meaningful Work	-0.27	0.07	1.70	0.09	-2.15	0.16	-0.08	0.04	0.38	0.02
F2. Risk Taking	-0.71	0.08	-0.82	0.11	-1.73	0.14	-0.38	0.05	0.46	0.03
F3. Customer Orientation	-0.47	0.11	-0.78	0.12	-1.27	0.24	-0.11	0.05	0.28	0.03
F4. Agile Decision Making	-0.67	0.08	-0.84	0.10	-1.61	0.14	-0.37	0.04	0.45	0.03
F5. Business Intelligence	-0.26	0.08	-0.34	0.10	-0.83	0.22	-0.16	0.05	0.20	0.03
F6. Open Communication	-1.09	0.08	-0.52	0.11	-1.78	0.11	-0.68	0.04	0.62	0.02
F7. Empowerment	-1.52	0.08	-0.24	0.09	-2.19	0.15	-0.14	0.04	0.49	0.02
F8. Business Planning	-0.33	0.08	-0.50	0.09	-0.92	0.21	-0.21	0.05	0.25	0.03
F9. Learning Organization	-0.34	0.09	-0.58	0.09	-0.97	0.23	-0.18	0.05	0.25	0.03

Note. Latent factor is the ICCS latent variable.

Tentatively, the following descriptions were made to differentiate the latent classes qualitatively:

- Latent Class 1 – Below Average, Low Empowerment
- Latent Class 2 – High Meaningful Work
- Latent Class 3 – Low Across the Board
- Latent Class 4 – Average
- Latent Class 5 – Above Average

The relationships among the demographic covariates and the latent profile solutions were examined using multinomial logistic regression methods and SAS's Proc Logistic program (SAS Institute, 2002 – 2003). All covariates (company membership, functional unit membership, organizational level, and organizational tenure) were dummy-coded into a set of indicator variables for each category of the demographic variables. The

dummy-coded variables were entered into the logistic regression equation to predict the LPA Model B (Including Outliers) class membership. Individual equations were calculated for each demographic variable using a block entry method. For each logistic equation, the reference category selected was the category with the highest proportion of cases.

For each equation, a significant global test statistic would indicate that the categories combine to predict class membership significantly. The global significance test results for the multinomial logistic regression analyses, in which class membership is independently predicted by demographic covariates, are presented in Table 64.

Table 64

Logistic Regressions Global Tests of Significance Results for Latent Profile Analysis (LPA) Model B (Including Outliers)

Demographic Covariate	Likelihood Ratio $\chi^2$	<i>df</i>	<i>p</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Three-Class Model						
Company	60.62	4	<.0001	58.81	4	<.0001
Functional Unit	58.81	9	<.0001	54.01	9	<.0001
Organizational Level	62.49	3	<.0001	58.49	3	<.0001
Organizational Tenure	13.24	5	0.0212	13.07	5	0.0227

Note. *N* = 1891.

All parameters were statistically significant, indicated by the Likelihood Ratio and Wald  $\chi^2$  tests of model fit. This indicates that company membership, functional unit membership, organizational level, and organizational tenure are each independently related to class membership solutions generated when Company A is included. To ensure that these results were approximately equivalent to the results generated for LPA Model A (Including Outliers) the logistic regression was conducted separately for this model using the same method described above. The global tests of model fit for each demographic covariate are presented in Table 65.

Table 65

Logistic Regressions Global Tests of Significance Results for Latent Profile Analysis (LPA) Model A (Including Outliers)

Demographic Covariate	Likelihood Ratio	<i>df</i>	<i>p</i>	Wald	<i>df</i>	<i>p</i>
Company	27.35	3	<.0001	27.29	3	<.0001
Functional Unit	29.71	9	0.0005	31.66	9	0.0068
Organizational Level	33.47	3	<.0001	26.05	3	<.0001
Organizational Tenure	7.33	5	0.1972	3.09	5	0.6857

Note. *N* = 1313.

For LPA Model A, the Likelihood Ratio  $\chi^2$  and Wald  $\chi^2$  for company membership, functional unit membership, and organizational level were statistically significant, but these tests for organizational tenure were not statistically significant. These results yield conclusions that duplicate those previously made for LPA Model A with the exception of the functional unit covariate, which was previously found to be not significant.

Because the global tests parallel the information considered for LPA Model A and model-fitting was not a goal of this analysis, the results for each category were not of interest. However, parameters and significance tests for these variables at the category level are provided in Appendix E.

### Outlier Comparisons Across Solutions

Because outliers were included in the data for the LPA Model B (Including Outliers) analysis, the distribution of outliers across the classes was of interest. The cases identified as multivariate outliers by class membership are presented in Table 66.

Although the frequencies of outliers in each class are approximately equal for both  $D_M$  and  $L$ , the proportion of cases in each sample identified as potential outliers varies widely. The Goodness-of-Fit test resulted in  $\chi^2(8) = 165.69, p < .001$ . The distribution of outliers across latent classes is not random. The smallest latent class, Latent Class 3, contains 9.1% potential outliers according to  $D_M$  and as much as 31.8% according to  $L$ . The profile for Latent Class 3 was characterized as “Low Across the Board.” The outliers

identified that belong to this class may indeed represent a small latent class; that is, they may be outliers in comparison to the entire dataset, but are legitimate scores inasmuch as they represent a small latent class.

Table 66

Frequencies of Outliers Identified by Mahalanobis Distances and Leverage Values Across ICCS Latent Classes for Latent Profile Analysis Model B (Including Outliers)

Class	<i>N</i>	<i>D<sub>M</sub></i>		<i>L</i>	
		<i>f</i>	%	<i>f</i>	%
1 – Below Average, Low Empowerment	188	4	2.1%	31	16.5%
2 – High Meaningful Work	106	4	3.8%	26	24.5%
3 – Low Across the Board	66	6	9.1%	21	31.8%
4 – Average	410	4	1.0%	21	5.1%
5 – High Across the Board	1121	4	.4%	40	3.6%

Note. *N* = 1891. *D<sub>M</sub>* is Mahalanobis Distance and *L* is the Leverage value.

**Class Comparisons.** A comparison of the class results for the solutions generated by LPA Model A (Including Outliers) and LPA Model B (Including Outliers) class results was conducted. The results are presented in Table 67. This analysis resulted in  $\chi^2(4) = 1158.79, p < .0001$ . For the two-class solution generated by LPA Model A (Including Outliers), of the 1243 assigned to the “Above Average” class, 61 cases were assigned to the Model B “High Meaningful Work” class, 295 to the Model B “Average” class, and 870 to the Model B “Above Average” class. Only 17 cases were assigned to the Model B “Below Average, Low Empowerment” or “Low Across the Board” classes.

Of the 175 cases assigned to the Model A “Below Average” class, all but 11 cases were assigned to the Model B “Below Average, Low Empowerment” or “Low Across the Board” classes. These results are statistically significant and conceptually congruent with expectations for cross-solution classification.

Table 67

Latent Class Assignments Among the LPA Model A (Including Outliers) and LPA Model B (Including Outliers) Solutions

LPA Model B (Including Outliers)	LPA Model A (Including Outliers) Class Assignment	
	1 - Above Average	2 - Below Average
1 – Below Average, Low Empowerment	15	115
2 – High Meaningful Work	61	0
3 – Low Across the Board	2	47
4 – Average	295	4
5 – Above Average	870	9

Note.  $N = 1418$ . Data in cells are observed counts.

Another comparison was made between the LPA Model B (Including Outliers) to the five-class solution generated for LPA Model B (Excluding Outliers). This comparison is presented in Table 68. There was generally good correspondence between these two solutions. One interesting finding is that for the dataset, including outliers, the members of the second latent class (High Meaningful Work) is dispersed among the two latent classes (Above Average and Below Average, Low Empowerment) from the outlier-free solution. Also, one solution in each class was labeled “Below Average, Low Empowerment” based on the shape and position of their profiles. However, no individuals were classified to both of these profiles. For the outlier-free dataset, this class is populated by cases from the “Average” class from the dataset that includes outliers.

In addition, a comparison of the LPA Model A (Including Outliers) and LPA Model A (Excluding Outliers) was conducted. The results are presented in Table 69. This analysis yielded  $\chi^2(1) = 1168.33, p < .0001$ . Only 15 cases (1.14%) were not classified into the “Above Average” or “Below Average” classes for both solutions. Clearly there is a high degree of correspondence between the two LPA Model A solutions (with and without outliers). Among all the profile solutions considered, with and without outliers, and for Model A and Model B analyses, there is considerable overlap in class assignment consistent with relative to average comparisons.

Table 68

Comparison of Latent Class Assignments for Five-Class Latent Class Solutions With and Without Outliers

Five-Class Solution (No Outliers)	Five-Class Solution (With Outliers)				
	1 - Below Average, Low Empowerment	2 -High Meaningful Work	3 -Low Across the Board	4 - Average	5 - Above Average
1 - Low Across the Board	28	0	28	1	0
2 - Below Average	129	6	17	45	52
3 - Below, Low Emp.	0	55	0	341	14
4 - Above Average	0	19	0	2	958
5 - High Across the Board	0	0	0	0	57

Note.  $N = 1752$ .

Table 69

Comparison of Latent Profile Analysis (LPA) Model A Class Assignments With and Without Outliers

LPA Model A (No Outliers)	LPA Model A (Including Outliers)	
	1 - Above Average	2 - Below Average
1 - Above Average	1161	1
2 - Below Average	14	137

Note.  $N = 1313$ .



**Appendix D: Demographic and Summary Data and Latent Profile Analysis (LPA)**

Table 70

## Frequency Data for Company Membership for Latent Profile Analysis (LPA) Model A Sample

Level	<i>f</i>	%
Company B	434	33.4
Company C	273	20.8
Company D – Time 1	260	19.8
Company D – Time 2 (Target Sample)	342	26

Note. *N* = 1313.

Table 71

## Frequency Data for Functional Unit Membership for Latent Profile Analysis (LPA) Model A Sample

Functional Unit	<i>f</i>	%
Business and General Management / Corporate	52	4.0
Supply Chain (Procurement, Customer Service, Operations Planning)	74	9.6
Manufacturing and Operations	481	46.2
Environmental Health and Safety	34	48.8
Human Resources	56	4.3
Marketing and Sales	255	19.4
Research and Development	174	13.3
Information Technology	56	4.3
Finance/Accounting/Legal	131	10.0

Note. *N* = 1313.

Table 72

## Frequency Data for Organizational level for Latent Profile Analysis (LPA) Model A Sample

Organizational Level	<i>f</i>	%
Non-manager	645	49.1
Manager	550	41.9
Executive	118	9.0

Note. *N* = 1313.

Table 73

## Frequency Data for Organizational Tenure for Latent Profile Analysis (LPA) Model A Sample

Organizational Tenure	<i>f</i>	%
Less than 1 Year	84	6.4
1 – 5 Years	417	31.8
6 –10 Years	214	16.3
11 – 15 Years	163	12.4
16 or More Years	435	33.1

Note. *N* = 1313.

Table 74

## Frequency Data for Company Membership for Latent Profile Analysis (LPA) Model B Sample

Level	<i>f</i>	%
Company A	381	21.7
Company B	451	25.7
Company C	283	16.2
Company D – Time 1	275	15.7
Company D – Time 2 (Target Sample)	362	20.7

Note. *N* = 1752.

Table 75

## Frequency Data for Functional Unit Membership for Latent Profile Analysis (LPA) Model B Sample

Functional Unit	<i>f</i>	%
Business and General Management / Corporate	53	3.0
Supply Chain (Procurement, Customer Service, Operations Planning)	76	4.3
Manufacturing and Operations	484	27.6
Environmental Health and Safety	34	1.9
Human Resources	56	3.2
Marketing and Sales	257	14.7
Research and Development	176	10.0
Information Technology	58	3.3
Finance/Accounting/Legal	132	7.5
Missing	426	24.3

Note. *N* = 1752.

Table 76

## Frequency Data for Organizational level for Latent Profile Analysis (LPA) Model B Sample

Organizational Level	<i>f</i>	%
Non-manager	892	50.0
Manager	684	39.0
Executive	156	8.9
Missing	20	1.1

Note. *N* = 1752.

Table 77

Frequency Data for Organizational Tenure for Latent Profile Analysis (LPA) Model B Sample

Organizational Tenure	<i>f</i>	%
Less than 1 Year	91	5.2
1 – 5 Years	469	26.8
6 – 10 Years	267	15.2
11 – 15 Years	225	12.8
16 or More Years	660	37.7
Missing	40	2.3

Note. *N* = 1752.

**Appendix E: Logistic Regression Parameter Estimates and Tests of Significance**

Table 78

Latent Profile Analysis (LPA) Model A Parameter Results for Logistic Regression Analysis of Class Membership on Company Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept	1.43	0.12	139.50	1	<.0001
Company C	1.11	0.26	18.01	1	<.0001
Company D – Time 1	1.06	0.26	16.29	1	<.0001
Company D – Time 2	1.07	0.24	20.28	1	<.0001

Note. *N* = 1313. Company A was not included in this analysis. Company C was the reference category.

Table 79

Latent Profile Analysis (LPA) Model A Parameter Results for Logistic Regression Analysis of Class Membership on Functional Unit Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept	1.82	0.13	190.69	1	<.0001
Business and General Management	1.40	0.73	3.65	1	0.0561
Supply Chain	-0.27	0.33	0.67	1	0.4121
Environmental Health and Safety	1.68	1.02	2.69	1	0.1012
Human Resources	1.05	0.61	3.00	1	0.0833
Marketing and Sales	0.23	0.24	0.98	1	0.3220
Research and Development	0.78	0.33	5.75	1	0.0165
Information Technology	0.50	0.49	1.07	1	0.3008
Finance/Accounting/Legal	0.01	0.29	0.00	1	0.9491

Note. *N* = 1313. Manufacturing and Operations functional unit was the reference category.

Table 80

Latent Profile Analysis (LPA) Model A Parameter Results for Logistic Regression Analysis of Organizational Level on Company Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept	1.59	0.12	229.19	1	<.0001
Manager	0.98	0.20	24.95	1	<.0001
Executive	2.47	0.72	11.74	1	0.0006

Note. *N* = 1313. Nonmanager was the reference category.

Table 81

Latent Profile Analysis (LPA) Model A Parameter Results for Logistic Regression Analysis of Tenure

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept	2.24	0.16	189.74	1	<.0001
Less than 1 Year	0.52	0.49	1.15	1	0.2839
1 – 5 Years	-0.27	0.22	1.48	1	0.2245
6 – 10 Years	-0.38	0.26	2.22	1	0.1366
11 – 15 Years	-0.43	0.28	2.40	1	0.1212

Note. *N* = 1313. Sixteen or More Years was the reference category.



Table 82

Latent Profile Analysis (LPA) Model B Parameter Results for Logistic Regression Analysis of Class Membership on Company Membership for Three-Class Solution

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-0.73	0.09	60.73	1	<.0001
Intercept2	-0.14	0.09	2.48	1	0.1157
Company A	-0.13	0.13	0.90	1	0.3420
Company C	-0.87	0.16	29.35	1	<.0001
Company D – Time 1	-0.32	0.15	4.54	1	0.0332
Company D – Time 2	-0.73	0.15	25.25	1	<.0001

Note. *N* = 1752. Company B was the reference category.

Table 83

Latent Profile Analysis (LPA) Model B Parameter Results for Logistic Regression Analysis of Class Membership on Functional Unit Membership for Three-Class Solution

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-0.85	0.09	84.79	1	<.0001
Intercept2	-0.26	0.09	8.65	1	0.0033
Business and General Management	-1.05	0.35	9.19	1	0.0024
Supply Chain	-0.17	0.25	0.49	1	0.4832
Environmental Health and Safety	-1.22	0.45	7.44	1	0.0064
Human Resources	-0.13	0.28	0.23	1	0.6323
Marketing and Sales	-0.34	0.16	4.74	1	0.0295
Research and Development	-0.84	0.19	18.79	1	<.0001
Information Technology	-0.17	0.28	0.37	1	0.5443
Finance/Accounting/Legal	-0.65	0.21	9.51	1	0.0020

Note. *N* = 1752. Manufacturing and Operations functional unit was the reference category.

Table 84

Latent Profile Analysis (LPA) Model B Parameter Results for Logistic Regression Analysis of Organizational Level on Company Membership for Three-Class Solution

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-0.83	0.07	141.82	1	<.0001
Intercept2	-0.24	0.07	13.48	1	0.0002
Manager	-0.43	0.10	17.32	1	<.0001
Executive	-1.29	0.22	34.80	1	<.0001

Note. *N* = 1752. Nonmanager was the reference category.

Table 85

Latent Profile Analysis (LPA) Model B Parameter Results for Logistic Regression Analysis of Class Membership on Company Membership for Three-Class Solution

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-1.34	0.08	185.31	1	<.0001
Intercept2	-0.56	0.08	49.80	1	<.0001
Less than 1 Year	-0.42	0.25	2.95	1	0.0859
1 – 5 Years	0.14	0.12	1.27	1	0.2592
6 – 10 Years	0.05	0.15	0.11	1	0.7387
11 – 15 Years	0.09	0.15	1.46	1	0.2266

Note. *N* = 1752. Sixteen or More Years was the reference category.

Table 86

Latent Profile Analysis (LPA) Model B Parameter Results for Logistic Regression Analysis of Class Membership on Company Membership for Five-Class Solution

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-3.08	0.15	410.01	1	<.0001
Intercept2	-1.23	0.10	163.29	1	<.0001
Intercept3	-0.12	0.09	0.04	1	0.8377
Intercept4	3.80	0.16	572.08	1	<.0001
Company A	-0.19	0.13	0.53	1	0.4675
Company C	-0.73	0.15	23.88	1	<.0001
Company D – Time 1	-0.46	0.15	9.90	1	0.0016
Company D – Time 2	-0.72	0.14	27.18	1	<.0001

Note. *N* = 1752. Company B was the reference category.

Table 87

Latent Profile Analysis (LPA) Model B Parameter Results for Logistic Regression Analysis of Class Membership on Functional Unit Membership for Five-Class Solution

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-3.27	0.15	459.22	1	<.0001
Intercept2	-1.42	0.10	220.85	1	<.0001
Intercept3	-0.22	0.09	6.53	1	0.0106
Intercept4	3.61	0.16	527.14	1	<.0001
Business / General Management	-1.21	0.32	14.60	1	0.0000
Supply Chain	-0.03	0.23	0.02	1	0.9012
Environmental Health and Safety	-0.23	0.39	9.81	1	0.0017
Human Resources	-1.22	0.28	0.96	1	0.3283
Marketing and Sales	-0.20	0.15	1.82	1	0.1773
Research and Development	-0.54	0.18	9.58	1	0.0020
Information Technology	-0.34	0.27	1.54	1	0.2133
Finance/Accounting/Legal	-0.30	0.19	2.44	1	0.1185

Note. *N* = 1752. Manufacturing and Operations functional unit was the reference category.

Table 88

Latent Profile Analysis (LPA) Model B Parameter Results for Logistic Regression Analysis of Organizational Level on Company Membership for Five-Class Solution

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-3.17	0.14	512.70	1	<.0001
Intercept2	1.31	0.07	309.80	1	<.0001
Intercept3	-0.10	0.07	2.42	1	0.1200
Intercept4	3.74	0.15	646.35	1	<.0001
Manager	-0.47	0.10	22.40	1	<.0001
Executive	-1.13	0.19	37.22	1	<.0001

Note. *N* = 1752. Nonmanager was the reference category.

Table 89

Latent Profile Analysis (LPA) Model B Parameter Results for Logistic Regression Analysis of Class Membership on Company Membership for Five-Class Solution

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-3.41	0.15	534.01	1	<.0001
Intercept2	-1.56	0.09	325.42	1	<.0001
Intercept3	-0.37	0.08	23.30	1	<.0001
Intercept4	3.41	0.15	533.62	1	<.0001
Less than 1 Year	-0.52	0.23	5.18	1	0.0228
1 – 5 Years	-0.02	0.12	0.03	1	0.8698
6 – 10 Years	-0.01	0.14	0.01	1	0.9437
11 – 15 Years	0.11	0.15	0.57	1	0.4512

Note. *N* = 1752. Sixteen or More Years was the reference category.

Table 90

Latent Profile Analysis (LPA) Model A (Including Outliers) Parameter Results for Logistic Regression  
Analysis of Class Membership on Company Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept	1.46	0.12	155.35	1	<.0001
Company C	1.00	0.25	16.44	1	<.0001
Company D – Time 1	0.70	0.23	9.66	1	0.0019
Company D – Time 2	0.83	0.22	14.81	1	<.0001

Note. *N* = 1419. Company A was not included in this analysis. Company C was the reference category.

Table 91

Latent Profile Analysis (LPA) Model A (Including Outliers) Parameter Results for Logistic Regression  
Analysis of Class Membership on Functional Unit Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept	1.77	0.12	202.76	1	<.0001
Business and General Management	1.53	0.73	4.38	1	0.0365
Supply Chain	-0.59	0.28	4.29	1	0.0383
Environmental Health and Safety	1.04	0.74	1.97	1	0.1608
Human Resources	0.85	0.53	2.57	1	0.1089
Marketing and Sales	0.18	0.22	0.68	1	0.4109
Research and Development	0.72	0.30	5.64	1	0.0175
Information Technology	0.84	0.53	2.46	1	0.1169
Finance/Accounting/Legal	0.15	0.29	0.28	1	0.5949

Note. *N* = 1419. Manufacturing and Operations functional unit was the reference category.

Table 92

Latent Profile Analysis (LPA) Model A (Including Outliers) Parameter Results for Logistic Regression  
Analysis of Organizational Level on Company Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept	1.59	0.10	243.08	1	<.0001
Manager	0.75	0.18	18.16	1	<.0001
Executive	1.45	0.43	11.33	1	0.0008

Note. *N* = 1419. Nonmanager was the reference category.

Table 93

Latent Profile Analysis (LPA) Model A (Including Outliers) Parameter Results for Logistic Regression  
Analysis of Class Membership on Company Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept	2.11	0.15	198.83	1	<.0001
Less than 1 Year	0.15	0.38	0.15	1	0.7022
1 – 5 Years	-0.22	0.21	1.19	1	0.2763
6 – 10 Years	-0.34	0.24	2.03	1	0.1545
11 – 15 Years	-0.21	0.27	0.66	1	0.4326

Note. *N* = 1419. Sixteen or More Years was the reference category.

Table 94

Latent Profile Analysis (LPA) Model B (Including Outliers) Parameter Results for Logistic Regression Analysis of Class Membership on Company Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-1.90	0.10	335.93	1	<.0001
Intercept2	-1.38	0.09	213.47	1	<.0001
Intercept3	-1.13	0.09	152.80	1	<.0001
Intercept4	-0.03	0.09	0.13	1	0.7299
Company A	-0.05	0.13	0.18	1	0.6694
Company C	-0.85	0.15	31.67	1	<.0001
Company D – Time 1	-0.33	0.14	5.68	1	0.0172
Company D –Time 2	-0.79	0.14	32.88	1	<.0001

Note. *N* = 1891. Company B was the reference category.



Table 95

Latent Profile Analysis (LPA) Model B (Including Outliers) Parameter Results for Logistic Regression Analysis of Class Membership on Functional Unit Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-2.04	0.10	389.34	1	<.0001
Intercept2	-1.52	0.09	262.55	1	<.0001
Intercept3	-1.27	0.09	196.61	1	<.0001
Intercept4	-0.17	0.08	4.21	1	0.0401
Business and General Management	-1.14	0.33	11.79	1	0.0006
Supply Chain	-0.06	0.22	0.08	1	0.7711
Environmental Health and Safety	-1.41	0.46	9.61	1	0.0019
Human Resources	-0.33	0.27	1.44	1	0.2297
Marketing and Sales	-0.26	0.14	3.32	1	0.0685
Research and Development	-0.78	0.18	18.36	1	<.0001
Information Technology	-0.40	0.27	2.10	1	0.1469
Finance/Accounting/Legal	-0.66	0.20	10.47	1	0.0012

Note. *N* = 1891. Manufacturing and Operations functional unit was the reference category.

Table 96

Latent Profile Analysis (LPA) Model B (Including Outliers) Parameter Results for Logistic Regression Analysis of Organizational Level on Company Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-1.96	0.09	521.34	1	<.0001
Intercept2	-1.45	0.07	375.44	1	<.0001
Intercept3	-1.20	0.07	286.35	1	<.0001
Intercept4	-0.10	0.06	2.40	1	0.1211
Manager	-0.48	0.10	24.54	1	<.0001
Executive	-1.26	0.20	40.28	1	<.0001

Note. *N* = 1891. Nonmanager was the reference category.

Table 97

Latent Profile Analysis (LPA) Model B (Including Outliers) Parameter Results for Logistic Regression Analysis of Class Membership on Company Membership

Variable	$\beta$	<i>SE</i>	Wald $\chi^2$	<i>df</i>	<i>p</i>
Intercept1	-2.25	0.10	533.56	1	<.0001
Intercept2	-1.74	0.09	397.43	1	<.0001
Intercept3	-1.49	0.08	318.43	1	<.0001
Intercept4	-0.41	0.08	29.97	1	<.0001
Less than 1 Year	-0.47	0.23	4.35	1	0.0369
1 – 5 Years	0.05	0.11	0.18	1	0.6743
6 – 10 Years	0.03	0.14	0.06	1	0.8004
11 – 15 Years	0.19	0.14	1.71	1	0.1913

Note. *N* = 1891. Sixteen or More Years was the reference category.

**Appendix F: Estimated Marginal Means for MANOVA Results**

Table 98

Estimated Marginal Means of ICCS Latent Factor Scores for Functional Unit Membership

DV	Functional Unit	<i>M</i>	<i>SE</i>	<i>LL</i>	<i>UL</i>
Meaningful Work	Business/General Management	0.39	0.16	0.077	0.703
	Supply Chain	0.118	0.128	-0.133	0.37
	Manufacturing and Operations	-0.083	0.11	-0.299	0.134
	Environmental Health and Safety	0.281	0.259	-0.226	0.789
	Human Resources	0.091	0.165	-0.232	0.414
	Marketing and Sales	0.055	0.088	-0.118	0.229
	Research and Development	0.386	0.109	0.172	0.600
	Information Technology	0.153	0.162	-0.164	0.471
	Finance/Accounting/Legal	0.041	0.132	-0.218	0.300
Risk Taking	Business/General Management	0.331	0.17	-0.001	0.664
	Supply Chain	0.079	0.136	-0.189	0.347
	Manufacturing and Operations	-0.125	0.117	-0.355	0.105
	Environmental Health and Safety	0.244	0.275	-0.296	0.784
	Human Resources	0.139	0.175	-0.205	0.483
	Marketing and Sales	-0.149	0.094	-0.333	0.035
	Research and Development	0.311	0.116	0.084	0.539
	Information Technology	0.205	0.172	-0.133	0.542
	Finance/Accounting/Legal	0.193	0.14	-0.082	0.468
Customer Orientation	Business/General Management	0.334	0.169	0.003	0.666
	Supply Chain	-0.003	0.136	-0.27	0.264
	Manufacturing and Operations	-0.21	0.117	-0.44	0.019
	Environmental Health and Safety	0.409	0.274	-0.129	0.947

Table 98 Continued

	Human Resources	0.169	0.175	-0.174	0.511
	Marketing and Sales	-0.039	0.094	-0.223	0.145
	Research and Development	0.199	0.116	-0.027	0.426
	Information Technology	0.094	0.172	-0.243	0.43
	Finance/Accounting/Legal	-0.029	0.14	-0.304	0.245
Agile Decision Making	Business/General Management	0.485	0.163	0.164	0.805
	Supply Chain	0.071	0.132	-0.187	0.329
	Manufacturing and Operations	-0.106	0.113	-0.327	0.116
	Environmental Health and Safety	0.498	0.265	-0.022	1.018
	Human Resources	0.25	0.169	-0.081	0.582
	Marketing and Sales	-0.045	0.091	-0.223	0.133
	Research and Development	0.298	0.112	0.079	0.518
	Information Technology	0.168	0.166	-0.158	0.493
	Finance/Accounting/Legal	0.154	0.135	-0.111	0.419
Business Intelligence	Business/General Management	0.413	0.158	0.103	0.724
	Supply Chain	-0.187	0.127	-0.437	0.063
	Manufacturing and Operations	-0.247	0.109	-0.462	-0.033
	Environmental Health and Safety	0.109	0.257	-0.395	0.613
	Human Resources	0.091	0.164	-0.229	0.412
	Marketing and Sales	-0.119	0.088	-0.291	0.053
	Research and Development	0.176	0.108	-0.036	0.388
	Information Technology	0.062	0.161	-0.253	0.377
	Finance/Accounting/Legal	-0.097	0.131	-0.354	0.159
Open Communication	Business/General Management	0.308	0.168	-0.021	0.638
	Supply Chain	0.034	0.135	-0.231	0.300

Table 98 Continued

	Manufacturing and Operations	-0.108	0.116	-0.336	0.12
	Environmental Health and Safety	0.358	0.273	-0.177	0.893
	Human Resources	0.215	0.174	-0.126	0.556
	Marketing and Sales	-0.029	0.093	-0.212	0.153
	Research and Development	0.274	0.115	0.049	0.5
	Information Technology	0.152	0.171	-0.183	0.486
	Finance/Accounting/Legal	0.159	0.139	-0.114	0.432
	Business/General Management	0.224	0.167	-0.104	0.552
	Supply Chain	-0.081	0.134	-0.345	0.183
	Manufacturing and Operations	-0.148	0.115	-0.374	0.079
Empowerment	Environmental Health and Safety	0.305	0.271	-0.227	0.837
	Human Resources	0.257	0.173	-0.082	0.595
	Marketing and Sales	-0.087	0.093	-0.268	0.095
	Research and Development	0.224	0.114	0	0.448
	Information Technology	0.167	0.169	-0.166	0.499
	Finance/Accounting/Legal	0.006	0.138	-0.265	0.277
	Business/General Management	0.496	0.165	0.173	0.819
	Supply Chain	0.034	0.133	-0.226	0.294
	Manufacturing and Operations	-0.163	0.114	-0.386	0.06
	Environmental Health and Safety	0.303	0.267	-0.221	0.827
Business Planning	Human Resources	-0.134	0.17	-0.468	0.200
	Marketing and Sales	0.011	0.091	-0.168	0.190
	Research and Development	0.122	0.113	-0.099	0.343
	Information Technology	0.251	0.167	-0.077	0.579
	Finance/Accounting/Legal	-0.025	0.136	-0.292	0.243

Table 98 Continued

Learning Organization	Business/General Management	0.29	0.165	-0.033	0.613
	Supply Chain	0.053	0.133	-0.207	0.313
	Manufacturing and Operations	-0.233	0.114	-0.456	-0.01
	Environmental Health and Safety	0.07	0.267	-0.455	0.594
	Human Resources	0.081	0.17	-0.252	0.415
	Marketing and Sales	-0.009	0.091	-0.188	0.170
	Research and Development	0.195	0.113	-0.025	0.416
	Information Technology	0.142	0.167	-0.186	0.469
	Finance/Accounting/Legal	0.031	0.136	-0.236	0.298

Table 99

Estimated Marginal Means of ICCS Latent Factor Scores for Organizational Level

DV	Organizational Level	<i>M</i>	<i>SE</i>	95% Confidence Interval	
				<i>LL</i>	<i>UL</i>
Meaningful Work	Non-Manager	-0.039	0.063	-0.163	0.084
	Manager	0.046	0.062	-0.076	0.169
	Executive	0.240	0.102	0.040	0.440
Risk Taking	Non-Manager	0.099	0.067	-0.033	0.230
	Manager	-0.025	0.066	-0.155	0.105
	Executive	0.190	0.109	-0.023	0.403
Customer Orientation	Non-Manager	-0.012	0.067	-0.143	0.119
	Manager	-0.059	0.066	-0.189	0.071
	Executive	0.155	0.108	-0.057	0.367
Agile Decision Making	Non-Manager	0.137	0.065	0.010	0.264
	Manager	0.027	0.064	-0.099	0.152
	Executive	0.237	0.105	0.031	0.442
Business Intelligence	Non-Manager	0.065	0.063	-0.057	0.188
	Manager	0.017	0.062	-0.104	0.139
	Executive	0.141	0.101	-0.058	0.340
Open Communication	Non-Manager	0.046	0.066	-0.084	0.177
	Manager	0.099	0.066	-0.031	0.228
	Executive	0.415	0.108	0.203	0.626
Empowerment	Non-Manager	0.004	0.066	-0.126	0.133
	Manager	0.140	0.065	0.012	0.268
	Executive	0.396	0.107	0.186	0.605



Table 99 Continued

Business Planning	Non-Manager	0.119	0.065	-0.008	0.247
	Manager	-0.033	0.065	-0.160	0.093
	Executive	-0.031	0.105	-0.237	0.176
Learning Organization	Non-Manager	0.000	0.065	-0.128	0.127
	Manager	-0.087	0.065	-0.213	0.040
	Executive	0.036	0.105	-0.171	0.243

Table 100

Estimated Marginal Means of ICCS Latent Factor Scores for Company X Level Interaction

DV	Company Membership	Organizational Level	<i>M</i>	<i>SE</i>	95% Confidence Interval	
					<i>LL</i>	<i>UL</i>
Meaningful Work	Company A	Non-Manager	-0.163	0.106	-0.370	0.045
		Manager	-0.106	0.123	-0.347	0.135
		Executive	0.170	0.176	-0.176	0.515
	Company B	Non-Manager	0.157	0.109	-0.057	0.370
		Manager	0.267	0.129	0.013	0.520
		Executive	0.391	0.228	-0.057	0.838
	Company C	Non-Manager	0.113	0.170	-0.221	0.446
		Manager	0.026	0.150	-0.267	0.319
		Executive	0.274	0.214	-0.145	0.693
	Company D (Time 1)	Non-Manager	-0.242	0.120	-0.477	-0.008
		Manager	-0.028	0.132	-0.286	0.231
		Executive	0.095	0.240	-0.376	0.567
	Company D (Time 2)	Non-Manager	-0.156	0.117	-0.386	0.074
		Manager	-0.067	0.101	-0.265	0.131
		Executive	0.210	0.141	-0.065	0.486
Risk Taking	Company A	Non-Manager	-0.019	0.113	-0.240	0.202
		Manager	-0.112	0.131	-0.368	0.144
		Executive	0.072	0.187	-0.295	0.440
	Company B	Non-Manager	0.116	0.116	-0.111	0.343
		Manager	-0.018	0.137	-0.288	0.252

Table 100 Continued

Customer Orientation	Company C	Executive	0.218	0.243	-0.257	0.694
		Non-Manager	0.327	0.181	-0.028	0.682
		Manager	-0.003	0.159	-0.315	0.309
	Company D (Time 1)	Executive	0.469	0.227	0.023	0.915
		Non-Manager	-0.110	0.127	-0.359	0.140
		Manager	-0.078	0.140	-0.353	0.196
	Company D (Time 2)	Executive	-0.043	0.256	-0.545	0.458
		Non-Manager	0.096	0.125	-0.148	0.341
		Manager	0.011	0.107	-0.199	0.221
		Executive	0.154	0.149	-0.139	0.447
	Company A	Non-Manager	0.149	0.112	-0.071	0.369
		Manager	0.153	0.130	-0.103	0.408
		Executive	0.065	0.187	-0.301	0.431
	Company B	Non-Manager	0.072	0.116	-0.155	0.298
		Manager	0.098	0.137	-0.171	0.367
		Executive	0.366	0.242	-0.109	0.840
	Company C	Non-Manager	0.471	0.180	0.117	0.825
		Manager	0.212	0.159	-0.099	0.523
		Executive	0.639	0.226	0.195	1.083
	Company D (Time 1)	Non-Manager	-0.433	0.127	-0.682	-0.185
		Manager	-0.322	0.140	-0.595	-0.048
		Executive	-0.363	0.255	-0.863	0.137

Table 100 Continued

	Company D (Time 2)	Non-Manager	-0.127	0.124	-0.371	0.117
		Manager	-0.218	0.107	-0.428	-0.009
		Executive	0.036	0.149	-0.256	0.328
Agile Decision Making	Company A	Non-Manager	-0.052	0.108	-0.264	0.161
		Manager	-0.158	0.126	-0.404	0.089
		Executive	0.052	0.180	-0.302	0.406
	Company B	Non-Manager	0.183	0.112	-0.036	0.402
		Manager	0.165	0.133	-0.095	0.425
		Executive	0.275	0.234	-0.184	0.733
	Company C	Non-Manager	0.515	0.174	0.173	0.858
		Manager	0.106	0.153	-0.195	0.406
		Executive	0.691	0.219	0.261	1.120
	Company D (Time 1)	Non-Manager	-0.158	0.123	-0.398	0.083
		Manager	-0.125	0.135	-0.390	0.139
		Executive	-0.176	0.246	-0.659	0.308
	Company D (Time 2)	Non-Manager	0.064	0.120	-0.171	0.300
		Manager	-0.012	0.103	-0.214	0.191
		Executive	0.221	0.144	-0.062	0.503
Business Intelligence	Company A	Non-Manager	0.260	0.105	0.054	0.466
		Manager	0.134	0.122	-0.105	0.373

Table 100 Continued

Open Communication	Company B	Executive	0.012	0.175	-0.330	0.355
		Non-Manager	0.198	0.108	-0.014	0.411
		Manager	0.092	0.128	-0.160	0.344
	Company C	Executive	-0.060	0.226	-0.504	0.384
		Non-Manager	0.429	0.169	0.098	0.760
	Company D (Time 1)	Manager	0.198	0.148	-0.093	0.489
		Executive	0.493	0.212	0.077	0.909
		Non-Manager	-0.250	0.119	-0.483	-0.018
		Manager	-0.068	0.131	-0.324	0.188
		Executive	0.003	0.239	-0.465	0.471
	Company D (Time 2)	Non-Manager	-0.098	0.116	-0.326	0.130
		Manager	-0.147	0.100	-0.343	0.049
		Executive	0.177	0.139	-0.097	0.450
	Company A	Non-Manager	-0.059	0.112	-0.277	0.160
		Manager	-0.153	0.129	-0.407	0.100
		Executive	0.177	0.186	-0.187	0.541
	Company B	Non-Manager	-0.017	0.115	-0.243	0.208
		Manager	-0.004	0.136	-0.272	0.263
		Executive	0.405	0.240	-0.066	0.877
	Company C	Non-Manager	0.233	0.179	-0.118	0.585
		Manager	0.122	0.158	-0.187	0.431
		Executive	0.685	0.225	0.243	1.126

Table 100 Continued

Empowerment	Company D (Time 1)	Non-Manager	-0.143	0.126	-0.390	0.104
		Manager	0.086	0.139	-0.186	0.358
		Executive	0.201	0.253	-0.296	0.698
	Company D (Time 2)	Non-Manager	0.142	0.124	-0.101	0.384
		Manager	0.218	0.106	0.010	0.427
		Executive	0.418	0.148	0.127	0.708
	Company A	Non-Manager	-0.062	0.111	-0.280	0.155
		Manager	-0.093	0.129	-0.345	0.159
		Executive	0.165	0.184	-0.197	0.526
	Company B	Non-Manager	-0.052	0.114	-0.276	0.172
		Manager	0.147	0.135	-0.119	0.413
		Executive	0.463	0.239	-0.006	0.932
Business Planning	Company C	Non-Manager	0.046	0.178	-0.304	0.396
		Manager	0.105	0.157	-0.202	0.412
		Executive	0.514	0.224	0.075	0.953
	Company D (Time 1)	Non-Manager	-0.092	0.125	-0.338	0.153
		Manager	0.198	0.138	-0.072	0.469
		Executive	0.385	0.252	-0.109	0.879
	Company D (Time 2)	Non-Manager	0.123	0.123	-0.118	0.364
		Manager	0.129	0.106	-0.078	0.336
		Executive	0.256	0.147	-0.033	0.544
	Company A	Non-Manager	0.120	0.109	-0.095	0.334

Table 100 Continued

		Manager	-0.077	0.127	-0.326	0.172
		Executive	-0.389	0.182	-0.746	-0.033
	Company B	Non-Manager	0.161	0.113	-0.060	0.382
		Manager	0.115	0.134	-0.146	0.377
		Executive	-0.314	0.236	-0.776	0.148
	Company C	Non-Manager	0.317	0.176	-0.027	0.662
		Manager	-0.123	0.154	-0.426	0.180
		Executive	0.407	0.221	-0.026	0.839
	Company D (Time 1)	Non-Manager	0.040	0.123	-0.202	0.282
		Manager	-0.100	0.136	-0.367	0.166
		Executive	-0.183	0.248	-0.670	0.304
	Company D (Time 2)	Non-Manager	-0.021	0.121	-0.258	0.217
		Manager	-0.030	0.104	-0.234	0.174
		Executive	0.048	0.145	-0.236	0.333
Learning Organization	Company A	Non-Manager	0.234	0.109	0.019	0.448
		Manager	0.110	0.127	-0.139	0.358
		Executive	-0.006	0.182	-0.363	0.350
	Company B	Non-Manager	0.198	0.113	-0.023	0.418
		Manager	0.168	0.133	-0.094	0.430
		Executive	0.052	0.236	-0.410	0.514
	Company C	Non-Manager	0.305	0.176	-0.039	0.650
		Manager	0.010	0.154	-0.293	0.313
		Executive	0.563	0.221	0.131	0.996

Table 100 Continued

Company D (Time 1)	Non-Manager	-0.333	0.123	-0.575	-0.091
	Manager	-0.349	0.136	-0.616	-0.083
	Executive	-0.348	0.248	-0.835	0.139
Company D (Time 2)	Non-Manager	-0.166	0.121	-0.403	0.071
	Manager	-0.187	0.104	-0.391	0.017
	Executive	-0.067	0.145	-0.351	0.218