Fall 2016

Using latent class cluster analysis to identify and profile organizational subclimates: An exploratory investigation using safety climate as an exemplar

Amy Frost Stevenson

USING LATENT CLASS CLUSTER ANALYSIS TO IDENTIFY AND PROFILE ORGANIZATIONAL SUBCLIMATES: AN EXPLORATORY INVESTIGATION USING SAFETY CLIMATE AS AN EXEMPLAR

by

Amy Frost Stevenson, B.A., M.A.

A Dissertation Presented in Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

COLLEGE OF EDUCATION

LOUISIANA TECH UNIVERSITY

November 2016

LOUISIANA TECH UNIVERSITY

THE GRADUATE SCHOOL

October 4, 2016

Date

We hereby recommend that the dissertation prepared under our supervision by Amy Frost Stevenson

entitled

Using Latent Class Cluster Analysis to Identify and Profile Organizational Subclimates: An Exploratory Investigation Using Safety Climate as an Exemplar

be accepted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy

Supervisor of Dissertation Research

Head of Department

Psychology and Behavioral Sciences

Department

Recommendation concurred in:

Advisory Committee

Approved:

Director of Graduate Studies

Dean of the College

Approved:

Dean of the Graduate School

GS Form 13a
(6/07)

ABSTRACT

Organizational climate refers to the shared meaning organizational members attach to the events, policies, practices, and procedures they experience as well as to the behaviors they see being rewarded, supported, and expected (Schneider, Ehrhart, & Macey, 2011). Climate scholars have most frequently used referent-shift consensus and dispersion composition models (Chan, 1998) to conceptualize and measure organizational climate. Based on these models, climate emergence has been characterized by low variance or high consensus of individual-level climate perceptions (Chan, 1998; Ehrhart, Schneider, & Macey, 2013; Hazy & Ashley, 2011; Kuenzi & Schminke, 2009) within formally defined organizational groups (e.g., work teams).

Climate scholars have begun to acknowledge these approaches may not offer adequate explanations for organizational-level perceptual variance patterns that could result from socially-derived influences such as demographic attribute similarity. Perceptual variance may instead be better explained by a patterned emergence compilation model (Fulmer & Ostroff, 2015), whereby nonuniform patterns of dispersion assume that skewness and/or multiple modes exist within the climate of an organization. Ostroff and Fulmer (2014) and Fulmer and Ostroff (2015) have proposed that configural measurement techniques such as latent class cluster analysis (LCCA; Nylund, Asparouhov, & Muthén, 2007) be used to identify subgroups of employees who perceive the organization similarly (i.e., subclimates). LCCA addresses the problems inherent in identifying subclimates via traditional composition models and measurement approaches,

but has yet to be used for this purpose. To address this gap, this exploratory study examined whether an organization may be usefully classified into subclimates, based on similarity of response patterns across safety climate dimensions. Subclimates were conceptualized as latent, unobserved groups characterized by systematic response patterns that exhibit within-group agreement and between-group differentiation, using LCCA to reveal five latent groups. Each distinct subclimate was subsequently examined for meaningful differences between them on profile characteristics and demographic attributes.

APPROVAL FOR SCHOLARLY DISSEMINATION

The author grants to the Prescott Memorial Library of Louisiana Tech University the right to reproduce, by appropriate methods, upon request, any or all portions of this Dissertation. It is understood that "proper request" consists of the agreement, on the part of the requesting party, that said reproduction is for his personal use and that subsequent reproduction will not occur without written approval of the author of this Dissertation. Further, any portions of the Dissertation used in books, papers, and other works must be appropriately referenced to this Dissertation.

Finally, the author of this Dissertation reserves the right to publish freely, in the literature, at any time, any or all portions of this Dissertation.

Author ____________________

Date 10/31/16

GS Form 14
(5/03)

DEDICATION

This dissertation is dedicated to my beloved daughter, Koy. Although you were not yet in my life when I began this journey, you are the sole reason for its completion.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

I would like to acknowledge the many individuals that have contributed to the successful completion of this dissertation. First, my committee was integral in shepherding me over the years, both in the attainment of knowledge and crystallization of that knowledge into a clear and achievable research goal. Dr. Mitzi Desselles was patient, yet provided the clarion voice needed to keep me moving forward during the numerous rough patches and major events of life. Thank you for sticking with me! Dr. Tilman Sheets always stressed the importance of "doing good work and doing it well." This is guidance I have internalized as a scientist and practitioner, and I cannot imagine a better mission to guide my future personal and professional endeavors. Dr. Jerome Tobacyk embodied, for me, a calming ethos that I could always count on to bring my stress levels down a notch. Discussing research with him always felt like a true exploration of ideas. Second, thank you to my friends Victoria, Cole, Ashley, and Megan for providing me with encouragement and much needed intermittent social distraction. Finally, a huge debt is due to my mother, Nelda; father, Dannie; brother, Eric; sister, Lacey; and husband, Josh. You have all provided a consistent support system and motivation. Your ever-present love and true faith in my abilities make the attainment of this goal joyous indeed.

CHAPTER 1

INTRODUCTION

Although organizational scholars have long acknowledged that social phenomena unfold in open, complex, and dynamic systems (Katz & Kahn, 1978), the complexity and dynamism of the social context that helps shape those systems have drastically changed in recent years (Johns, 2006). Globalization—propelled by the tripartite forces of increased economic liberalization, falling trade barriers, and massive advancements in technology—has led to the blurring of traditional geographic and corporate boundaries. A more diverse organizational ecosystem now exists, in which the amalgam of employees who constitute modern organizational workforces is challenging what we know about how behavior is a function of both the person and the environment (Lewin, 1936).

Over many years of research and hundreds of studies, organizational climate has been shown to exert powerful influences on both organizations and employees and has important implications for outcomes at the individual (Colquitt, Noe, & Jackson, 2002; Ehrhart, 2004; McKay, Avery, & Morris, 2008), team (Pirola-Merlo, Härtel, Mann, & Hirst, 2002), and organizational (Schulte, Ostroff, & Shmulyian, & Kinicki, 2009) levels. As a reflection of perceptions organizational members share regarding policies, practices, and procedures, organizational climate is a group-level construct that conceptualizes the way individuals experience their work settings (Schneider et al., 2011). Although research on organizational climate continues to proliferate, leading climate scholars have voiced concerns that the field is increasingly fragmented (Kuenzi & Schminke, 2009) and myopically focused on measurement concerns at the expense of theoretical development and conceptual evolution (Ehrhart et al., 2013).

Given the increasing complexity of the organizational ecosystem, there have been calls to examine whether organizational climate is integrated and unifying, as traditionally conceptualized, or whether multiple, differentiated climates are more common within modern organizations (Schneider & Barbera, 2014). Organizational theory provides several views that suggest the consistency among organizational policies, practices, and procedures may vary widely within a single organization. For example, the rational view of organizations suggests stability, or consistency, among policies, procedures, and practices (Blau & Scott, 1962; Weber, 1947). Conversely, Cohen, March, and Olsen (1972) characterized organizations as organized anarchies and Weick (1979) as loosely coupled systems. When considered in light of the socially-derived nature of organizational climate, these theories suggest that organizations can establish elements and processes that seem inconsistent or mutually exclusive to employees, depending on how they are operationalized in the context of one's work. Perceptual inconsistencies can thus result in significant within-company variation in climate perceptions between groups (Zohar & Luria, 2005).

An impediment to studying within-company perceptual variation is that the models most frequently used as frameworks for conceptualizing and measuring organizational climate are not conducive to identifying multiple climates within a single organization. Briefly, organizational climate is conceptualized as a socially-shared, group-level variable that captures an aggregation of subjective perceptions of individuals regarding their work environment (Schneider, 2000). Researchers have historically used a consensus composition model (Chan, 1998) as a basis to conceptualize and measure organizational climate. When using a consensus composition model, organizational climate is viewed as the mean of subjective perceptions of a group or an organization, with groups typically referring to formalized, sub-organizational groups such as departments, work teams, or branches. The mean of subjective perceptions is a measurement parameter referred to as climate level, which may be alternatively construed as a measure of central tendency. More specifically, climate level may be designated as low or high, depending on the relative position of the organizational or group average to the negative (i.e., low) or positive (i.e., high) end of the response scale. For a given climate level to meaningfully represent a group or organization as a whole, and for organizational climate to conceptually exist, those perceptions must be shared (Schneider, 2000). In order to indicate that perceptions are indeed shared, an acceptable level of agreement or consensus must be statistically demonstrated (LeBreton & Senter, 2007). The demonstration of consensus serves to legitimize the aggregation of individual, subjective climate perceptions to higher levels of analysis at the group and organizational level (James, 1982; James, Demaree, & Wolf, 1984, 1993).

Given the centrality of consensus as a key requirement for legitimizing aggregation of climate perceptions, the subject of variability was panned as theoretically uninteresting by Guion (1973). However, climate researchers eventually began to question the sensibility of rigid cutoff guidelines dictating that group climate levels (e.g., means) of less than 100 percent agreement were not valid indicators of the existence of organizational climate (Chan, 1998). Some researchers went further, and suggested that variability in of agreement could in fact be conceptually valuable to study, rather than strictly a statistical prerequisite for aggregation (Lindell & Brandt, 2000). The introduction by Chan of dispersion composition models provided climate researchers a framework to conceptualize the degree of within-group agreement of scores from individual-level climate measures as a measurement construct called climate strength (Bliese & Halverson, 1998; Colquitt et al., 2002; González-Romá, Peiró, & Tordera, 2002; Klein, Conn, Smith, & Sorra, 2001; Kozlowski & Klein, 2000; Schneider, Salvaggio, & Subirats, 2002). Climate strength may be defined as the extent to which member perceptions within a group or organization are aligned with each other, such that the greater the alignment, the stronger the climate is said to be (Schneider et al., 2002). The operationalization of climate strength is based on dispersion measures, such as variance, standard deviation, average absolute deviation, coefficient of variation, and, most frequently, the $r_{wg(j)}$ statistic (Bliese, 2000; James et al., 1984; James & Jones, 1974). Just as climate level may be alternatively construed as a measure of central tendency, climate strength may be thought of as a measure of dispersion that reflects variability of climate perceptions within a group or organization. More specifically, the climate strength measurement parameter allows climate researchers to quantify the amount of shared meaning present in a group or organization (Dickson, Resick, & Hanges, 2006; Zohar & Luria, 2005).

In their comprehensive review of the organizational climate literature, Kuenzi and Schminke (2009) note that although the study of climate strength holds great potential for further understanding of the climate construct, there is a need to break from the narrow focus on the work group or department as the unit of analysis and to extend the examination of consensus and variability to the organizational level. They further explain that concentration on the work-unit is reflective of an historical tendency to fixate on within-workgroup agreement to justify aggregation, but is not conducive to studying climate strength at the organizational level. That is, speaking of organizational climate as a meaningful construct at the organizational level would seem to imply consensus across all organizational units; likewise, speaking of a strong climate at the organizational level would seem to imply a common set of perceptions pervade the organization. However, empirical data has indicated the existence of significant and patterned variation in climate perceptions within organizations (Dawson, González-Romá, Davis, & West, 2008; Dickson et al., 2006; Zohar & Luria, 2005). The work of Zohar and Luria is particularly noteworthy in that they introduced a between-units model of safety climate dispersion based on the notion that variation in mean climate levels between groups is non-random and therefore meaningful and that climate strength is negatively related to between-groups variability. Safety climate may be defined as perceptions shared among employees regarding organizational policies, procedures, and practices as they relate to the value and priority of safety within an organization, as well as the safety-related behaviors that get rewarded and supported (Zohar, 1980). While Zohar and Luria's climate variability data suggested discrepant group climates, they used formalized work units as the level of measurement in their dispersion model, which may have, in turn, masked important response patterns at the organizational level. Returning to the idea that multiple, differentiated climates may be more common within modern organizations (Schneider & Barbera, 2014), the work of Zohar and Luria supports the argument that lower levels of between-unit agreement may not necessarily indicate a complete lack of consensus and may instead be indicative of multiple subclimates within which there may be significant agreement and within which member climate perceptions coalesce into similar response patterns on climate measurement scales (Ehrhart et al., 2013). Subclimates are groups characterized by high climate strength (e.g., within-group alignment among members' perceptions) and significant between-group discrimination. Importantly, subclimates do not necessarily correspond to formalized work groups. Subclimate group members may instead exhibit similarities in attributes such as functional or occupational background (Martin, 2001; West, Topakas, & Dawson, 2014). By limiting the study of climate strength to only formalized groups (e.g., work teams) in which the majority of members agree (e.g., traditional within-group agreement indices), climate researchers like Zohar and Luria risk overlooking important patterns of differential group functioning (Ehrhart et al., 2013) as well as the possibility that multiple, differentiated climates exist in organizations. Further, the continuing focus on work teams as the unit of analysis may impede a more accurate examination of climate strength at the organizational level (Kuenzi & Schminke, 2009).

It is worth noting that from both a conceptual and methodological standpoint the identification and study of subclimates presents some difficulties. First, the use of dispersion composition models as a conceptual foundation for organizational-level climate strength calls for the use of variability statistics (González-Romá & Peiró, 2014). Variability statistics, however, will not allow for the identification of subclimates since variability statistics assume unimodal distributions of climate scores (Chan, 1998). By definition, subclimates are multimodal manifestations (West et al., 2014). Second, dispersion models typically specify the use of intact suborganizational groups (e.g., work teams, departments) as group-level measurement boundaries when assessing organizational-level climate strength. This presents a conceptual hurdle when speaking of subclimates, which often do not conform to these boundaries.

Recently, researchers have suggested reframing the study of variability in climate perceptions as the study of divergence and have put forth an alternative model whereby variability is assumed to be systematically patterned, such that the configuration of perceptions as identified by response patterns may in fact represent a compilation form of organizational climate emergence (Fulmer & Ostroff, 2015; Ostroff & Fulmer, 2014). The comprehensive perspective of the configural compilation model lends itself to examining climate outside the traditional boundaries of work groups and departments and thus, would be more appropriate than dispersion models for identifying subclimates. Although configural techniques have not been used to identify subclimates per se, configural techniques such as cluster analysis have previously been utilized to examine response patterns on dimensions of molar (i.e., generic) organizational climate (Ostroff, Kinicki, & Tamkins, 2003). Studies have shown that particular configurations of response are related to organizational effectiveness (Schulte et al., 2009), which suggests utility in considering climate configurations. Furthermore, configural techniques have been used to identify subgroups and collective climates (i.e., conceptually similar to subclimates) that perceive the organization similarly based on climate survey response patterns (González-Romá, Peiró, Lloret, & Zornoza, 1999; Patterson, Payne, & West, 1996).

Ostroff and Fulmer (2014) and Fulmer and Ostroff (2015) have proposed that the use of configural measurement techniques popular within the organizational culture literature may aid in the identification and examination of groups that exhibit similar climate response patterns. Latent class cluster analysis (LCCA; Nylund et al., 2007) is a configural measurement technique that could be used to address the problems inherent in identifying and studying subclimates. For the purposes of identifying subclimates, LCCA offers several distinct advantages over cluster analysis. First, unlike cluster analysis LCCA is model-based. Thus, the criteria generated for assessing and selecting cluster solutions is less arbitrary. Second, the criteria and tests (e.g., Lo-Mendell Rubin test, parametric bootstrapped likelihood ratio test) available for making decisions about the number of latent classes (e.g., subclimates) are more formalized (Lo, Mendell, & Rubin, 2001; Nylund et al., 2007). Third, the model-based nature of LCCA lends itself to both exploratory and confirmatory applications (Wang & Hanges, 2011). Given the current lack of availability of climate typologies (Ehrhart et al., 2013), the exploratory utility of LCCA to examine subclimates is apparent. Finally, LCCA is very flexible with regard to data, and supports the use of mixed mode data (Bacher, 2000). This is particularly important, as subclimates are multi-modal manifestations (West et al., 2014). By conceptualizing subclimates as latent groups characterized by systematic response patterns that exhibit within-group agreement and between-group differentiation, and by using LCCA to reveal those latent groups, this research contributed to an exploratory examination of organizational climate outside the boundaries of traditional work groups and departments. Broadly, LCCA would allow for the classification of an organization into sublimates based on similarity of response patterns across climate dimensions. The response patterns of distinct subclimates (e.g., that exhibit high climate strength and significant between-group differentiation) could then be examined to identify meaningful differences between them in terms of characteristics such as demographic attributes.

The study of subclimates using LCCA is valuable for several reasons. First, the use of LCCA to identify subclimates entails the examination of unaggregated organizational-level data, which avoids concerns that the use of work groups and departments as standard organizational subaggregations may not be the most appropriate level of analysis when examining organizational level climate strength (Kuenzi & Schminke, 2009). Second, the examination of within-subclimate response distributions and agreement statistics at the item level could assist in the identification of issues that may be helpful to target when designing intervention plans to strengthen organizational climate (Bliese, 2000). Third, the exploratory use of configural techniques like LCCA would support the development of organizational climate profiles and typologies, which have both practical and theoretical utility and have been largely ignored by climate researchers (Schulte et al., 2009).

The work of Zohar and Luria (2005) supports an argument that that lower levels of between-unit agreement may not necessarily indicate a complete lack of consensus and may instead be indicative of multiple subclimates within which there may be significant agreement and within which member climate perceptions coalesce into similar response patterns on climate measurement scales (Ehrhart et al., 2013). As such, safety climate provides a sensible vehicle to conduct a preliminary exploratory application of LCCA to examine safety subclimates.

Early Climate Research: 1939-1975

In order to establish the argument that LCCA can be used to identify and study safety subclimates, it is necessary to understand the history of organizational climate and the development of commonly used climate measurement models. Research on organizational climate evolved out of a more widespread interest in understanding how situations influence behavior (Hellriegel & Slocum, 1974). The Hawthorne studies, which provided substantiation for the socio-psychological influence of the work context on employees and their performance (Mayo, Roethlisberger, & Dickson, 1939; Roethlisberger, 1941), are often heralded as a seminal turning point in the approach to modeling human behavior in organizations. In particular, these studies demonstrated that the social situation and context within which employees work affect both employee attitudes and productivity. The Hawthorne studies ushered in a social context-sensitivity movement in industrial psychology that paralleled a more widespread departure from the strict individual differences models that had been up to that point prevalent in general psychology (Ehrhart et al., 2013). Psychologists soon began to use the term climate as a label to explain the effects of situational influences on behavior, like those found in the Hawthorne studies.

The term climate was formally introduced to the psychological domain by Lewin, Lippitt, and White (1939), whose work on social climates was predominantly focused on the effects of leadership styles on social behavior. Their perspective, aligned with findings from the Hawthorne studies, was that individual behavior was a function of the person and the environment. When investigating the role of democratic, autocratic, and laissez-faire leadership styles on the functioning and performance of groups, Lewin and colleagues examined the levels of aggression within groups and how the atmosphere, or social climate, that emerged affected aggressive behaviors. Three features of their work are worth noting. First, a major focus of the research was on the social climate characterized by interactions of group members. Second, leadership style was conceptualized as a proximal antecedent of group-level climate. Finally, their observations of member interactions were focused on the groups as a whole, rather than on individual differences among group members. Since many psychologists of the time were focused on the examination of individual differences, relatively few were focused on how the work context might factor into the person-environment equation. Soon after World War II, however, scholars in both psychology and management followed in the footsteps of Lewin and colleagues, and began to address the potential influence of the social context in organizations (Fleishman, 1953; Argyris, 1957, 1958; Leavitt, 1959; McGregor, 1960; Likert, 1961; Schein, 1965). Organizational climate research soon gained wider popularity within both scholarships.

1970s: Major Critiques

Throughout the 1950s and 1960s, climate researchers tended to rely on the conceptual model of social climates as put forth by Lewin et al. (1939) whereby specific leadership styles create specific types of climates, which then result in specific behavioral responses from groups. Similar to Lewin and colleagues, other early climate researchers (Fleishman, 1953; Likert, 1961; McGregor, 1960) studied climates with a particular emphasis (e.g., leadership climate, managerial climate). However, there was a shift in the late 1960's toward investigating the entire content domain of organizational climate, rather than a specific aspect like leadership. This more holistic view of conceptualizing climate is known as molar climate. Molar climate enthusiasts viewed organizational climate as being a set of generic, measurable properties of the work environment that are perceived by organizational members and assumed to influence their motivation and behavior (Campbell, Dunnette, Lawler, & Weick, 1970). The prevailing assumption at that time was that employees who experienced a positive general climate would be more likely to exhibit superior performance. By focusing on assessing the contextual attributes of the work environment associated with employees feeling positive about their work setting, molar climate measurement scales attempted to capture how people-oriented the climate of an organization was (Schneider & Bartlett, 1968, 1970).

Schneider and Bartlett (1968) were among the first to voice concerns over the broad and amorphous nature of the molar climate construct. Likewise, other climate researchers began to question how best to conceptualize and define climate (Litwin & Stringer, 1968; Tagiuri, 1968), what the dimensionality of climate might be (Evan, 1968; Litwin & Stringer, 1968; Meyer, 1968), whether organizations could have multiple climates (Evan, 1968; Meyer, 1968), and whether climate was in fact relevant for predicting specific organizational effectiveness outcomes (Litwin & Stringer, 1968). These questions raised interest in theoretical and conceptual issues, as well as fueled several important critiques that would ultimately serve to focus and orient organizational climate researchers for years to come. For example, Litwin and Stringer noted that the subjective and perceptual nature of climate would yield an "infinite variety of organizational climates" (p. 45). When developing a molar climate scale, Schneider and Bartlett (1968, 1970) questioned the breadth organizational climate measures would need to exhibit to accurately capture the dimensions of the total climate space. Finally, Campbell and colleagues (1970) questioned whether climate was in fact being conceptualized as an individual attribute, as opposed to an organizational attribute as originally conceptualized by Lewin and colleagues (1939), whether climate was best measured using objective or subjective perceptual approaches, and whether climate could be conceptualized as a direct predictor of organizational performance.

Lack of conceptual clarity. To understand how the field of organizational climate began to organize and address such questions, it is helpful to review the critiques that subsequently emerged in the wake of Campbell and colleagues' (1970) review. The critiques by Guion (1973), Johannesson (1973), and James and Jones (1974) are particularly noteworthy because the issues raised therein forced climate researchers to address specific problems with regard to conceptual clarity, scale validation, differentiation from affective-oriented constructs, inconsistencies in the climate-outcome relationship, and measurement.

Guion (1973) most forcefully argued there was a lack of conceptual clarity regarding climate. He argued that there was no conceptual standard in place to guide whether climate should be studied as an attribute of the organization, as it was originally conceived by Lewin and colleagues (1939), or as an attribute of the individual. Calling organizational climate "one of the fuzziest concepts to come along in some time" (p. 121), he opined that many climate researchers, were studying climate at the individual level of analysis out of methodological convenience and strong individual differences orientations. The lack of conceptual clarity, coupled with the tendency to study climate at the individual level of analysis, led to climate being frequently measured at what Guion viewed as the improper level of analysis.

James and Jones (1974), of the individual differences orientation, were active in commenting on Guion's critique on the proper level of theory and level of analysis for organizational climate studies. They argued for emphasizing the individual as the basic unit of climate theory based on the opinion that variance in climate perceptions "is a function of differences between individuals and is not necessarily descriptive of organizations or situations" (p. 1103). More specifically, James and Jones conceptualized climate as a process that intervenes between the individual-level processing of organizational attributes and the respective development and exhibition of employee attitudes and behaviors. They therefore defined climate as the individual-level, personal perceptions of the social setting or context to which an individual belongs. This construct came to be known as psychological climate (Jones & James, 1979).

Hellriegel and Slocum (1974), in response to Guion (1973) and in opposition to James and Jones (1974), argued that the bulk of climate history and literature had clearly supported the conceptualization of climate as an attribute of the organization, rather than as an attribute of individuals. They defined organizational climate as a shared, emergent, unit-level phenomenon derived from the aggregation of individual perceptions and used to represent the climate of larger units of analysis (e.g., organizations and their subsystems). Although James and Jones disagreed and viewed the individual as the focal unit of climate theory, they did propose that conceptual disagreements could be avoided if researchers took care to theoretically distinguish psychological (e.g., individual-level) climate from organizational (e.g., unit-level) climate. This proposition was important in that it supported the clarification of conceptualization of the organizational climate construct and allowed a transition in focus toward related measurement issues (Schneider, 2000).

Lack of validation against objective organizational measures. Along with criticisms regarding a lack of conceptual clarity, Guion (1973) and James and Jones

(1974) also questioned the established precedent that climate be measured perceptually, arguing that such measurements resulted in an inability to validate organizational climate against objective measures of reality. Their concern was that objective measures such as turnover and accidents would not be subject to filtration through individual perceptual lenses and, would thus be more accurate measures of the organizational reality being perceived. Other climate scholars rejected this criticism, stressing that the objective facets of the work setting are not the climate, but rather climate is the meaning attached to the experiences of the work setting (Schneider, 1975). In their review of climate research, Hellriegel and Slocum (1974) agreed, noting that "to the extent a climate researcher has a strong interest in understanding and anticipating the human component within organizations, it is probably desirable to employ perceptual measures" (p. 260).

Correlation with outcomes of interest. In addition to concerns about a lack of conceptual clarity and lack of validation against objective organizational metrics, researchers were concerned that organizational climate had not shown an ability to correlate with relevant outcomes of interest. Of primary concern was that the focus of much early research on organizational climate was on employee well-being rather and satisfaction rather than measures of organizational effectiveness. In a detailed review of climate measures and studies investigating the relationship between organizational climate and performance outcomes, Hellriegel and Slocum (1974) concluded that for those studies that did examine the relationship between climate and performance, the relationship was inconsistent. Conversely, they found consistent relationships between climate and satisfaction, which led to concerns that climate may not be differentiated from affective evaluations and work attitudes like job satisfaction (Schneider & Snyder, 1975).

Lack of differentiation from affective evaluations and attitudes. The focus by researchers on the measurement of individual well-being and satisfaction, in particular, resulted in the dimensionality of organizational climate being reflective of personal experiences rather than descriptive of the organizational setting. This, in addition to the consistent relationships found between climate and satisfaction, led Guion (1973) and Johannesson (1973) to question whether the construct of organizational climate overlapped attitudes like job satisfaction. In response, other researchers stressed the importance of differentiating between descriptions of the work environment and personal evaluations of one's job situation, with the former distinguishing organizational climate and the latter distinguishing affective appraisals associated with job attitudes (Hellriegel & Slocum, 1974; Payne, Fineman, & Wall, 1976; Schneider, 1975; Schneider & Snyder, 1975).

Lack of consensus in ratings of organizational climate. Finally, Guion (1973) questioned how a lack of consensus in ratings of organizational climate by organizational members should be considered with regard to measurement and aggregation procedures. He argued that to form meaningful macro-level climate indices, aggregated individual-level data could not exhibit variance, as variance would necessarily indicate less than 100 percent agreement of climate perceptions and, thus, would not be indicative of a shared reality. Vigorous debates over the role and importance of variance in climate measurement would subsequently continue for decades.

Responses

In an attempt to address the major critiques and unresolved issues, Schneider (1975) wrote an essay outlining his support for the construct and provided a proposal for a cohesive path for future climate research. Addressing the inconsistencies found in research studies between organizational climate and performance, he explained that the amorphous nature of molar climate resulted in the development of measurement scales that often included too many dimensions. He suggested that the ever-increasing number of dimensions made it difficult to tailor measurement in a way that would uncover correlations between organizational climate and outcomes other than well-being. In a departure from the established molar approach, he argued that the criterion of interest should instead drive what content was included in climate scales so that climate correlates or predictors would then be linked both conceptually and operationally to more specific outcomes. He further argued that by conceptualizing climate as focused on descriptions of organizational events regarding specific organizational goals or processes (e.g., service, safety), and by relating them to applicable outcomes of interest (e.g., customer satisfaction, accidents), that a more focused climate approach would alleviate many of the most heavily cited issues (Schneider, Parkington, & Buxton, 1980; Zohar, 1980). Schneider explained that unlike molar climate scales, focused climate scales would be less similar to general attitudinal measures and would therefore be more likely to uncover relationships with variables other than general satisfaction or well-being. He argued that focused climate conceptualizations would allow the multitude of climate dimensions to be narrowed to those most relevant for predicting related outcomes of interest. Regarding the practical utility of climate, he noted that when dimensions are narrowed and scale items related to specific goals and processes within an organization, the relationship between focused climate and the related outcome would be strengthened both empirically and conceptually. Finally, when addressing the critiques regarding the appropriate levels of analysis at which to conduct climate research, Schneider agreed that researchers had not been taking care to aggregate variables to the appropriate level of analysis. More specifically, he believed researchers were not ensuring that the level of analysis of the criterion being used was aligned with the level of analysis of the collection and examination of data. Schneider suggested that improper alignment could have led to the inconsistencies in relationships found by Hellriegel and Slocum (1974) since climate may show stronger or weaker relationships at different levels, depending on the particular outcome being used.

Modern Climate Research: 1976-2016

Following its introduction by Lewin and colleagues (1939), the concept and study of organizational climate has evolved greatly. By the mid-1960s there was increased interest in empirical examination of the concept. However, definitional disagreement and confusion between the level of the theory and the level of data gathered and analysis undertaken soon led to several influential critiques (Schneider et al., 2011). Major critiques articulated concerns regarding whether climate was an attribute of the individual or of the organization (Guion, 1973; James & Jones, 1974), whether there was overlap between climate and job attitudes (Johannesson, 1973; Schneider & Snyder, 1975), and whether consistent relationships with organizationally-relevant outcomes could be found (Hellriegel & Slocum, 1974). Several researchers, including Hellriegel and Slocum (1974), James and Jones (1974) and Schneider (1975), provided reviews and replies that stressed the importance of distinguishing between psychological and organizational climate and in clearly delineating the most appropriate level of analysis for criteria and data collection. Schneider's responses to the critiques were fundamental in that they not only offered answers to difficult questions, but in that they also charted the course of subsequent climate research. His observations regarding the need to align the level of measurement and the level of analysis heavily influenced debate and research on climate measurement and subsequent levels of analysis issues. His responses also contributed to progress on the clarification of the definition of organizational climate and offered substantiation for the application of statistics such as r_{WG_j} (James & Jones, 1974) to justify aggregation of climate perceptions to the unit level. By supporting a return to the early approach of studying specific climates (Lewin et al., 1939; Fleishman, 1953; McGregor, 1960) to increase construct validity, Schneider also advocated for what eventually became known as the focused climate approach that is dominant in organizational climate research today.

Following Schneider's (1975) essay, climate research slowed during the 1980s and 1990s. This slowdown has been primarily attributed to lingering disagreement between psychological and organizational climate-oriented psychologists over the appropriate level of theory and appropriate level of data and analysis from which to conceptualize and conduct climate studies (Schneider et al., 2011). During the 1980s, research interest shifted instead toward the construct of organizational culture (Pettigrew, 1979), presumably, in the words of Schneider, Ehrhart, and Macey (2013), due "to the fact that it seemed to capture the richness of the organizational environment in ways that climate research had not" (p. 363). Additionally, organizational culture research perspectives were attractive to climate researchers precisely because levels of analysis issues did not pose a problem, since the collective was the sensible unit of analysis and individual differences were therefore irrelevant (Schneider et al., 2011). After an interlude, research on organizational climate gained popularity again, and now largely eclipses the number of studies on culture.

Modern Conceptualizations of Climate

Modern conceptualizations of organizational climate have benefited from the rich history of critiques and responses by early climate scholars such that the key conceptual attributes and definition of the construct have been extensively refined and clarified (Schneider, 2000). Renewed interest in climate research has been attributed to several advancements that addressed the earlier critiques and, in so doing, provided a clearer investigative pathway for a new generation of climate researchers (Ehrhart et al., 2013). First, the definition of organizational climate has been extensively clarified. Now that an accepted distinction has been made between organizational- and individual-level climate perceptions (James et al., 2008; Ostroff et al., 2003), organizational climate is now widely regarded as an aggregate, unit-level attribute (Chan, 1998; Kozlowski & Klein, 2000; Ostroff et al., 2003) and researchers increasingly specify level-adjusted perceptions when defining and measuring the construct (Chan, 1998; Kozlowski & Klein, 2000; Zohar, 2010). Second, there is general agreement that matching the bandwidth and focus of measures and outcomes improves the validity of climate research as well as the understanding of the contexts that are likely to bring about specific, focused climates (Burke, 2011). This advancement is due to continuation by climate researchers in the steps of Schneider (1975), who advocated for studying climates and outcomes focused on specific aspects of the organizational context (e.g., service, safety). Empirical support for the focused climate approach has increased conceptual understanding of the antecedents and consequences of the construct, as well as extended its practical usefulness to a wider audience (Schneider, 2000). Third, research has consistently shown that focused organizational climate is linked to a variety of important organizational outcomes at individual, group, and organizational levels (Kuenzi & Schminke, 2009). Finally, organizational climate research has advanced enough to support the investigation of multi-level modeling and cross-level relationships (Schulte et al., 2009; Zohar & Luria, 2005), using more sophisticated measurement parameters (Schneider et al., 2002).

Key conceptual attributes. In their recent writings on the history and current state of organizational climate research, Ehrhart and colleagues (2013) endorsed the following modern definition of climate:

> Organizational climate is the shared meaning organizational members attach to the events, policies, practices, and procedures they experience and the behaviors they see being rewarded, supported, and expected. Organizational climate is an abstraction that represents the cognitive structuring of a whole out of many observations and experiences; the whole is the meaning attached to those many observations and experiences. Thus, climate is conceptually an abstraction about the meaning of a setting for the members that experience it. (p. 2)

This definition is exemplary for several reasons. First, in line with the writings of Schneider and Reichers (1983) on the etiology of climates, it accounts for the constituent inputs and processes related to both the person (James, James, & Ashe, 1990) and the situation (Katz & Kahn, 1978). Thus, this definition captures the conceptualization of climate from a social-interactionist perspective (Berger & Luckmann, 1967) and considers the wider context of the organization (Johns, 2006) as an open social system (Katz & Kahn, 1966). More important, this definition makes explicit the role of the shared meaning attached by organizational members to their perceptions and experiences, which is considered a key conceptual attribute (Schneider, 2000). To succinctly summarize conceptual commonalities found in modern definitions of organizational climate, Ehrhart, Schneider, and Macey distilled the following five attributes:

1. The emergence of organizational climate occurs via numerous mechanisms (e.g., social mechanisms such as leadership, communication, social interaction, training, and structural mechanisms such as system strength, organizational context, internal consistency of policies, practices, and procedures.).
2. The mechanisms are not climate. Rather, the experiences that the mechanisms produce, and the meaning attached to those experiences, are climate.
3. Organizational climate is not an individual-level property. It is a group-level property of units and/or organizations, based on shared experiences and shared meaning.
4. Shared experiences and shared meaning derive from interactions in units and/or organizations.
5. Organizational climate is a descriptive abstraction of experiences at work and the meaning attached to those experiences by organizational members. It is not an affective evaluation of the work environment (e.g., satisfaction).

Chan's (1998) compositional typology. While the development of statistical indicators of agreement and guidance on their use (Schneider, 1975) was a large step toward resolving the levels of analysis debate (Schneider et al., 2011), questions began to surface whether climate would remain isomorphic (i.e., identical) across levels (Klein, Dansereau, & Hall, 1994; House, Rousseau, & Thomas-Hunt, 1995). Full resolution to the levels of analysis debate did not occur until frameworks were developed for clarifying multilevel conceptualizations and deciding on measurements for climate at multiple levels of analysis (Chan, 1998; Morgeson & Hofmann, 1999; Kozlowski & Klein, 2000). The framework most frequently used by climate researchers for this purpose is Chan's (1998) typology of composition models.

Chan's compositional typology (1998) is derived from the work of James (1982), who defined compositional models as "the specification of how a construct operationalized at one level of analysis is related to another form of that construct at a different level of analysis" (p. 220). More recently, Chan (2014) defined compositional models as "specifying functional relationships between constructs at different levels, including how variables at a lower level may be aggregated in different ways to compose the construct at higher levels (p. 486). Chan's original typology included five forms that compositional models may take, three of which are heavily used by climate researchers when conceptualizing and operationalizing organizational climate. These five forms are: (a) additive, (b) direct consensus, (c) referent-shift consensus, (d) process and (e) dispersion.

Additive models specify that group constructs are a result of the summation of lower level variables, regardless of the variance among those groups (e.g., aggregation of psychological climate perceptions to represent organizational climate). Aggregation is accomplished by simply averaging the individual-level climate perceptions to form a mean organizational climate score. In consensus models, both direct and referent-shift, within-group agreement of scores from lower-level measures is used to index consensus. The mean of individual-level responses within a group is used, after meeting selected cutoff criteria for within-group agreement, to represent the group's value on climate. That is, where there is high agreement at the lower-level, aggregation to represent variables at higher levels is considered justified. With direct consensus models, the group construct is specified by consensus among the lower-level variables. Within-group consensus at lower levels is used as specification for how a construct conceptualized and operationalized at a lower level of analysis could be functionally isomorphic as one at higher levels. The direct consensus approach to measurement is favored by individual-level oriented (i.e., psychological) climate researchers who emphasize the individual as the primary unit of theory (Glisson & James, 2002; James et al., 2008) and when climate survey items tend to assess personal affect or opinions of the organizational environment (e.g., I have the tools and resources necessary to provide efficient service.). Conversely, referent shift models specify that there is a distinction between original lower-level variables and those formed by consensus. That is, the referent of climate survey items in this case is shifted from the individual to the group, and the resulting construct is assumed to be shared by group members (e.g., In my group we have the tools and resources necessary to provide efficient service.). Organizational climate researchers have most often used the referent-shift consensus model to compose organizational climate, arguing that this approach is most appropriate since items developed with a referent-shift will correctly refer to the level to which individual climate responses will be aggregated, as well as result in improved consensus upon aggregation (Bliese, 2000;

LeBreton & Senter, 2007). Process models specify that process parameters are analogous at multiple levels. A process model for climate formation, for example, would outline how the process of psychological (i.e., individual) climate development is analogous to group- and organizational-level climate emergence. Finally, dispersion models specify that the variance of lower-level variables is the meaning of the group-level construct (Brown & Kozlowski, 1999; Kozlowski & Klein, 2000). That is, dispersion models conceptualize the degree of within-group agreement of scores from the lower-level measure as a construct of interest in its own right, rather than strictly a statistical prerequisite for aggregation (Chan, 1998; Kozlowski & Klein, 2000).

Measurement Parameters

In addition to specifying functional relationships between constructs at different levels, compositional models have also been heavily relied upon to assist in operationalizing climate measurement parameters from the individual to the group and organizational levels. Chan's (1998) referent-shift consensus model and dispersion composition model, in particular, provide the framework for two aggregated constructs called climate level and climate strength. The two constructs are distinct in their definitions and measurement implications, yet both are derived from the same individual-level climate perceptions.

Climate level. Climate level may be defined as a unit-level rating of climate perceptions (Zohar & Luria, 2005). In the majority of climate studies, the mean value of individual perceptions of the organizational climate are calculated and if aggregation is statistically justified based on established values (Bliese & Halverson, 1998; Chan, 1998; James, 1982; Klein et al., 1994), individual-level climate scores are then aggregated to yield a unit-level climate rating. When speaking of a focused climate, like safety climate, climate level reflects the level of perceived organizational priority for safety (Zohar, 2010). Alternatively, climate level may be construed as a measure of central tendency. That is, climate level may be designated as low or high, essentially referring to the relative position of the organizational or group average to the negative (i.e., low) or positive (i.e., high) end of the response scale. With a focal climate, then, a high climate level would typically indicate a higher perceived priority for the respective focal facet, while a low score would indicate a lower perceived priority (Schneider et al., 2011; Zohar & Tenne-Gazit, 2008).

Another issue central to fostering resurgence of climate research was the clarification of circumstances under which the aggregation of individual-level data to higher levels of analysis (e.g., unit or organization) is appropriate (Bliese, 2000). As previously noted, one of the major critiques of early climate research was what role consensus played in climate measurement (James & Jones, 1974). Specifically, many researchers had questioned how variability in climate ratings should be considered with regard to legitimizing aggregation, to include concerns with the most appropriate methods and indices to be used in calculations of within-group agreement (Guion, 1973).

James (1982) was particularly integral in clarifying the issue of consensus. In 1984, James and colleagues developed the r_{WG} index, which is an index of interrater agreement for a group. The r_{WG} index is calculated by comparing an observed group variance with an expected random variance. For the r_{WG} index, a value of .70 is frequently invoked as the cutoff level required to justify aggregation. However, this value has been criticized as arbitrary, and it has become standard practice to compute interrater reliability indices such as intraclass correlation coefficients to facilitate aggregation decisions (Ehrhart et al., 2013). More specifically, the r_{WGj} statistic is often coupled with the use of interclass correlations (ICC) to aid in the assessment whether the aggregation of climate scores is justified (Bliese, 2000). The most frequently used ICCs used for this purpose are the interrater agreement ICC(1) and interrater reliability ICC(2) statistics. When speaking of climate, interrater agreement addresses the extent to which members provide the same absolute ratings of a climate. When members provide the same rating, then their ratings would be interchangeable. By contrast, interrater reliability addresses the extent to which, across members, rank ordering of ratings are consistent. Two separate, but related, measures are frequently used by climate researchers to assess both interrater agreement and interrater reliability of climate perceptions. ICC(1) is the percentage of variance explained by the unit. When there is low variability within units and high variability across units, high ICC(1) scores will result. However, if there is high variability within units or low variability across units, ICC(1) will be negatively affected. ICC(2) is an index of the reliability of group means (Bliese, 2000). When using both interrater agreement and interrater reliability indices, aggregation is considered justified when there is both high interrater agreement and high interrater reliability (Bliese, 2000).

Although several other agreement statistics are available, including the average deviation (AD) index (Burke, Finkelstein, & Dusig, 1999), aWG (Brown & Hauenstein, 2005), and within and between analysis (WABA; Dansereau, Alutto, & Yammarino, 1984), the r_{WG} statistic is still the most common indicator used by climate researchers to report within-group agreement (LeBreton & Senter, 2007). Even though the joint use of the r_{WGj} statistic and ICC(1) and ICC(2) are now standard practice when calculating and interpreting aggregation statistics, there is some disagreement over whether all three are needed. In particular, George and James (1993) argued that aggregation is conditional only on there being agreement within-groups, not differences across groups. This debate has largely been resolved by the development of Chan's (1998) compositional typology, which allows for the specification of the climate construct via various models (Chan, 1998; Kozlowski & Klein, 2000) that dictate the conceptualization and measurement of the focal variables.

A more widespread and current debate has been whether researchers should apply strict cutoffs to aggregation statistics when interpreting them (Lance, Butts, & Michels, 2006; LeBreton & Senter, 2007). Rather than using the strict, and arguably arbitrary, cutoff of .70 for r_{WGj}, LeBreton and Senter argued that it is more sensible to interpret scores on a continuum along which researchers may group responses as no agreement (0.00 to 0.30) to moderate agreement (0.51 to 0.70) to strong agreement (0.91 to 1.00). Similarly, they recommended interpreting ICC(1) values as an effect size, with 0.01 being a small, 0.10 a medium, and 0.25 a large effect size. The complexity of interpretation of aggregation statistics does not end with the application of cutoffs. Table 1 presents three scenarios that illustrate the complexity of such issues that must be considered by researchers as well as related considerations and recommendations.

Table 1

Justifying the Aggregation of Climate, based on Adequate Interrater Agreement and Reliability

Scenario	Standard	Consideration	Recommendation
Weak aggregation statistics	Average r_{WGj} higher than .70 or ICC(1) values greater than .10	May be of conceptual interest; may indicate differentiated climates	Do not necessarily remove groups with low agreement; examine overall pattern of agreement across all groups in dataset (Kaufman & Rousseeuw, 2009; LeBreton & Senter, 2007)
Within-unit sample size variability	Target minimum within-group response rates 20%-30%	High within-group agreement may provide justification that sample is providing meaningful representation of views of unit	Consider including small samples that exhibit high within-group agreement (Newman & Sin, 2007)
Dictating appropriate level of analysis	ICC(1) values of .10 or greater	Nested structures may be present and should be accounted for	Calculate ICC(1) values for each level to determine the appropriate target level(s) of analysis (Zohar & Luria, 2005)

Although established analytical justifications for aggregation are heavily relied upon, climate researchers have begun to stress the importance of explicating the linkages between theoretical rationale and analysis for aggregation decisions (Kozlowski & Klein, 2000). For example, Ehrhart and colleagues (2013) advocate for the consideration of organizational context when establishing relationships between the level of theory and the level of groups being studied (e.g., the structure of groups and nature of their work). Further, researchers suggest that the simplistic application of cutoff scores with traditional aggregation statistics may be inadvisable, given that there may be instances and contexts in which the use of lower or higher standards may be advisable (LeBreton & Senter, 2007). In a related vein, if the level of theory and units under analysis are well-justified, researchers have advocated for the examination of weaker aggregation statistics before assuming analysis at the focal level is inappropriate. In such an instance, Ehrhart and colleagues advocate for the use of an assessment based on an overall pattern of agreement across all groups in a dataset. In this way, a researcher may also consider if variability of within-group agreement may be conceptually of interest (Kaufman & Rousseeuw, 2009), and therefore worthy of further examination. These issues all merit thoughtful consideration and may, as Bliese (2000) noted, require judgment calls on the part of the climate researcher. Although there is little argument that climate, as an aggregate indication of shared meaning, requires statistical demonstration that meaning is shared, researchers now have several options to calculate and interpret indicators of consensus and need not rely solely on strict cutoff scores.

Climate strength. In contrast to the consensus model used as a basis for legitimizing aggregation, dispersion theory (Brown & Kozlowski, 1999) and dispersion models (Chan, 1998) allowed for the consideration of climate not only in terms of means, but also in terms of variability. More specifically, dispersion models specify that the meaning of a group-level construct is derived from the variance of lower-level variables (Kozlowski & Klein, 2000). When speaking of measurement parameters for organizational climate, dispersion models conceptualize the degree of within-group agreement of scores from the individual measure of climate as a construct of interest in its own right. Indicated by the statistical characteristic of consensus in organizational climate research (Evan, 1968; Lindell & Brandt, 2000), the degree of within-group agreement among member perceptions of climate is a construct referred to as climate strength (Schneider et al., 2002). Climate strength may be defined as the extent to which member perceptions within a group are aligned with each other (González-Romá et al., 2002). Alternatively, climate strength may be thought of as a measure of dispersion reflecting variability of climate perceptions within a unit. The climate strength measurement parameter allows climate researchers to quantify the amount of shared meaning present in a group, and is key to understanding the nature and operation of organizational climate in organizations (Schneider et al., 2011; Zohar, 2010).

The operationalization of climate strength is based on dispersion measures and homogeneity statistics (e.g., variance, standard deviation, average absolute deviation, $r_{wg(j)}$, coefficient of variation), such that the greater the demonstration of group consensus the stronger the climate is said to be (LeBreton & Senter, 2007; Schneider et al., 2002). With regard to standards of use, there have been arguments to support the use of standard deviation over the r_{wg} homogeneity statistic when calculating climate strength. Bliese (2000) noted that the use of r_{wg} overlooks practical and theoretical concerns related to the use of the uniform distribution as the null distribution since the null distribution assumes no response bias and that each response option is equally likely to be selected on a Likert scale (LeBreton & Senter, 2007; Likert, 1967), therefore not accounting for expected random variance (Brown & Hauenstein, 2005). Further, the frequently used rectangular distribution does not take into account the predominance of using restricted segments of response ranges (Zohar & Tenne-Gazit, 2008). Finally, the use of r_{wg} can lead to difficulty in interpretation and overestimation of the degree of agreement based on the likelihood of resulting in values greater than one (Schneider et al., 2002).

It is important to note that caution should be used when interpreting climate levels based on the amount of within-group variance (e.g., climate strength) that is present. For example, if within-group variance is high (e.g., indicating a weak climate), the group mean of climate scores is more unreliable, and may thus not be an appropriate measure of climate level for the group. Thus, the group mean (i.e., climate level) would not be a meaningful measure of central tendency if high levels of variance exist. This has led to the recommendation that researchers should make efforts to obtain construct validity evidence for climate strength rooted in processes of climate emergence (Chan, 2014).

Composition and Compilation Models of Climate Emergence

The processes by which individual perceptions coalesce to emerge as organizational climate may differ with regard to their distinct aspects and forms. Leveraging the compositional typology framework of Chan (1998), Kozlowski and Klein (2000) developed a comprehensive typology of emergence to guide the conceptual treatment of multilevel and aggregation issues and to explicate differences between composition and compilation emergent processes. More specifically, in their model composition emergent processes assume isomorphism in terms of construct similarity across levels of analysis. When speaking of organizational climate emergence, the essential features of a composition process are convergence and sharedness of perceptions among sub-organizational aggregates. Conversely, compilation emergent processes assume discontinuity in terms of differences in the structure of the construct across levels of analysis. In this case, the essential features of a compilation process of organizational climate emergence would be variability and configuration among sub-organizational aggregates. Relating their conceptualization of emergent processes to Chan's typology, Kozlowski and Klein explained that additive, direct-consensus, and referent-shift consensus composition models are consistent with composition processes, while dispersion and process composition models are consistent with compilation processes. The relevance of this emergence typology is that it allows for viewing climate emergence along a continuum, along which six forms of climate emergence (e.g., convergent, pooled constrained, pooled unconstrained, minimum/maximum, variance, and patterned) may be conceptualized.

Patterned Emergence

In composition forms of climate emergence, the end result of the emergent process is assumed to exhibit low variance or consensus of individual-level elements (Chan, 1998; Hazy & Ashley, 2011), such that within-group variability is considered as indicative of a weaker climate. However, consensus does not always occur within the confines of suborganizational aggregations (e.g., departments) and perceptions may diverge systematically across the organization (Fulmer & Ostroff, 2015). Kozlowski and Klein's (2000) compilation model of patterned emergence helps to explain these phenomena. The authors state that "This model incorporates the assumption that emergence may manifest itself as different forms, and it views nonuniform patterns of dispersion as meaningful substantive phenomena" (p. 41). Importantly, a uniform distribution assumes a single mode, and indicates either strong or weak agreement. Conversely, a nonuniform distribution assumes high skewness or multiple modes, and indicates either strong or weak disagreement.

In organizational culture, Fulmer & Ostroff's (2015) proposition that variability may be systematically patterned is not new. In an effort to understand the factors that might prevent or inhibit relationships between organizational culture and organizational effectiveness, organizational culture researchers have investigated similar systematic differences in perception (Scott, Mannion, Davies, & Marshall, 2003). Recent work by Lok, Rhodes, and Westwood (2011) and West and Spendlove (2006) on professional variation in organizational culture in healthcare settings has shown that nurses can have different culture experiences than physicians in the same settings, and that perceptual differences emerge from occupation-specific norms and training. Their findings further indicated that subcultures act as the mechanism through which organizational culture influences employee outcomes.

Martin and Siehl (1983) and Martin (1992, 2001) are organizational culture researchers who have been active in promoting the idea that multiple cultures and climates can exist within an organization, such that clusters of people could emerge with different or unique experiences, and that differentiated subcultures and subclimates can affect organizational functioning and effectiveness. Organizational subcultures can be defined as "a group or unit in an organization that is in frequent interaction, which perceives itself to be distinct from other groups in the organization, and that shares similar problems as well as in-group understanding of ways of solving such problems" (Morgan & Ogbonna, 2008, p. 42). In their original conceptualization, Martin and Siehl categorized subcultures as either enhancing, orthogonal, or countercultures. Enhancing subcultures can be described as those that are aligned with and amplify the dominant culture of an organization, through fervent support of fundamental values, artifacts, and beliefs. Orthogonal subcultures exist as an intersection between the two, whereby a subculture simultaneously coexists with the dominant organizational culture yet holds idiosyncratic (e.g., occupation-specific), non-conflicting values. Finally, countercultures are those that are active in their opposition to the established, or dominant, culture.

Martin (2001) outlined three competing perspectives that serve as a framework for understanding how organizational culture may be differentiated into subcultures. Although she recognizes the legitimacy of the widely held integrationist conceptualization of culture, which stresses that culture can in fact be shared throughout the organization, she advocates for two other perspectives as a more realistic norm. The fragmented view denies the property of sharedness absolutely, stressing that individual member differences (e.g., hierarchical level, occupation, personality) would necessarily preclude the shared experience of organizational events and thus, similarity in the meaning attached to those events. Alternatively, the differentiation perspective, considered a compromise between the integrationist and fragmented views, assumes that all aspects of an organization's culture are not necessarily shared and that members belong to subcultures. Subcultures are often delineated by categorical attributes such as job function, occupation, and gender. Subculture members are thought to share perceptions and values that differ from other subculture groups or even the organization as a whole. As a result of subculture membership, members may experience different events or may attach different meanings to the events experienced by all members of the organization.

Martin (2001) argues that there are frequently multiple differentiated climates in organizations and, as such, the integrationist perspective is most unusual. More recently, Martin, Frost, and O'Neill (2006) described three characteristics that, if observed in an organization, would substantiate the differentiated viewpoint of organizational culture. That is, if there are inconsistencies of member interpretations across the organization, consensus limited to subculture boundaries, and clarity existing only within subcultures, the organizational culture can said to be differentiated (e.g., not unitary).

Research findings have indicated that subculture development can result from drivers such as physical proximity, similarities in tasks or status (e.g., occupation or hierarchical level), and workflow dependencies (Van Maanen & Barley, 1985) as well as from similarities in age, ethnicity, and education (Trice & Beyer, 1993). Similar to organizational climate, these factors can contribute to more regular interaction, which helps to develop collective understandings and interpretations of organizational events as well as a sense-making system that drives the development of normative behaviors. In an investigation of organizational culture of an urban police department, Jermier, Slocum, Jr., Fry, and Gaines (1991) used cluster analysis to investigate subcultures. The authors found five distinct clusters, or subcultures, that were associated with structural variables (e.g., rank, departmental assignment, and shift), individual variables (e.g., tenure), and outcome variables (organizational commitment and performance). Only one of the five subcultures identified was found to be closely aligned with what was defined as the official organizational culture, lending support to the differentiation perspective developed and promoted by Martin (1992, 2001).

In Organizational Climate

Recently, climate researchers have advocated for the conceptualization of climate as a differentiated phenomenon, citing the work of Martin (2001) as an applicable framework (Schneider & Barbera, 2014). Similar to Martin, who views multiple, differentiated cultures rather than one integrated and unified organizational culture as the norm within organizations, climate differentiation advocates view organizations as having multiple climates that can be identified and differentiated by examining variability more closely. There are two frameworks that may be used to explain and investigate climate differentiation. The first view conceptualizes climate differentiation as a function of the level in the organization. That is, organizational climate may be interpreted as a multi-level phenomenon with sources of climate perceptions relating, respectively, to the organizational and group level of analysis. In recent years, advances in multi-level modeling techniques (Kozlowski & Klein, 2000), in concert with the increased use of level-adjusted climate scales, have supported the examination of main and cross-level effects of climate of both the work group and organization on outcomes of interest (Zohar, 2000; Zohar & Luria, 2005). The second, and less frequently invoked, view is that variability in organizational climate perceptions may be patterned, and related to functional and occupational differences rather than level. In the past, this framework has been used as the basis for examining collective climates (Joyce & Slocum, 1984).

Collective climates can be defined as aggregated individual climate perceptions based on groupings or clusters that exhibit similarity in perceptions (James, 1982). González-Romá and colleagues extended the work of Joyce and Slocum (1984) by testing the validity of the collective climates concept. Collective climates were originally proposed by Joyce and Slocum to overcome issues with obtaining within-group agreement to justify aggregation in formally defined sub-organizational aggregates (e.g., department, hierarchical level, and work team). With collective climates, agreement must be demonstrated among climate perceptions of individuals in the same cluster, rather than formally defined suborganizational aggregates. The concept and meaning of collective climates was criticized by Payne (1990) for only demonstrating that clustering techniques work, rather than demonstrating that clusters have conceptual utility for understanding the functioning of organizations. He argued that for collective climates to be meaningful social constructs, researchers had to demonstrate that perceptual agreement within each cluster was based on a formal or informal structured collective with a socio-psychological identity.

In a quest to understand the conditions most likely to elicit strong versus weak climates, researchers have begun to amass considerable evidence that climate strength is subject to social influence (Dickson et al., 2006, González-Romá, Fortes-Ferreira, & Peiró, 2009; Schneider et al., 2002; Zohar, 2010; Schneider et al., 2013). That social influence could affect perceptual consensus is not a new notion. In 1938, Barnard emphasized that groups are defined and understood through a system of interactions and that through those interactions uniform states of mind can come to exist. Pressure toward attaining uniformity, as explained by social comparison theory (Festinger, 1954), is driven by the need to interpret reality. When the organizational environment is complex or ambiguous, individuals tend to turn toward their social networks or referents for interpretive assistance.

Organizational theory literature defines symbolic interactionism as a process by which meaning and reality are socially construed via cognitive exchanges among people seeking to understand their environment (Blumer, 1986; Stryker, 1980). In other words, meaning and interpretation of the organizational environment arise from an interplay between individual perceptions and the perceptions of others in similar situations. Perceptions are continuously checked and modified against referent's observations and assessments. Symbolic social interaction involves individuals making comparisons and discussing interpretations and the meaning of events, procedures, and practices at work. As workers engage in this interaction over time, individual perceptions converge (Schneider & Reichers, 1983). The emergence of climate is promoted by convergence in that group members begin to share interpretations and meanings of their organizational environments.

A more recent conceptualization of symbolic interactionism has been labeled social sense making. Sense making refers to an ongoing interpretive process by which individuals engage in social exchanges in order to make sense of complex and ambiguous work situations (Weick, 1979, 1995; Weick, Sutcliffe, & Obstfeld, 2005). The precedent of using formally defined suborganizational aggregates, such as work teams, as a grouping variable in climate research is largely based on the argument that members of work units interact more frequently and are subject to the same supervisory messages and actions related to policies, practices, and procedures (Zohar, 2010). Through social comparison, sensemaking, and symbolic social interaction processes, team members are thus expected to share a similar understanding of the norms and expectations associated with the climate (Weick, 1995) and to exhibit higher climate strength. Indeed, Huang and colleagues (2013) contend that because group members are apt to interact more often with each other than with individuals in other groups, they are more likely to develop shared perceptions of both the unit climate as well as the global organizational climate. However, social comparison theory also guides the argument that individuals utilize as a referent group those who are similar to them. According to the principles of homophily, individuals who share demographic characteristics are more likely to share similar histories, narratives, experiences, and attitudes, which facilitates interaction and smooths communication (McPherson, Smith-Lovin, & Cook, 2001). There is a basis, then, for the argument that demographic similarity, rather than formalized suborganizational aggregates, may be the fulcrum upon which social comparison and symbolic social interaction yields strong shared perceptions. It follows that clusters of employees that exhibit similarity in perceptions may indeed be a meaningful social construct and may have conceptual utility for understanding the emergence of organizational climate from an alternative perspective.

Returning to the arguments of Martin (2001) that systematic perceptual differences emerge from clusters of employees as well as to the emergence typology of Kozlowski and Klein (2000), patterned emergence may provide a better context for understanding climate differentiation in organizations. Recently, Fulmer and Ostroff (2015) proposed that perceptual divergence, as signified by low climate strength, indicates the presence of a patterned form climate emergence similar to Kozlowski and Klein's model (Fulmer & Ostroff, 2015; Kozlowski & Klein, 2000; Ostroff & Fulmer, 2014). They argue that the almost exclusive use of Chan's (1998) dispersion model as a basis to conceptualize and measure climate strength has limited the study of divergence. They note that dispersion models are limited in that they focus singularly on the degree of convergence or variability of perception. In other words, dispersion models rely on the variance form of emergence, whereby emergence is based on uniform distributions of within-group dispersion. More specifically, dispersion models specify that low dispersion indicates consensus, while high dispersion indicates divergence. Although dispersion does represent variability across individuals, Ostroff and Fulmer argue that variability is better viewed as patterned or configured, such that variability represents a new compilation form of emergence, rather than simply divergence. In this case, emergence could be based on nonuniform distributions of within-group variance that is indicated by the formation of multiple modes that correspond to suborganizational aggregate clusters.

Subclimates

When examining organizational-level climate distributions, the presence of multimodality may indicate that there are pronounced groups based on similar patterns of response (Bacher, 2000). The groups identified by modes and response patterns are thought to correspond to subclimates (West et al., 2014). Subclimates are groups characterized by high climate strength and significant between-group discrimination (Martin, 2001). When studying perceptual equivalence of the meaning of safety climate in groups, Bergman (2011) noted that when climate is examined at the organizational level, within-group agreement indices may not be the most appropriate descriptor of organizational-level climate strength. That is, when referencing a strong climate at the organizational level, one would infer agreement about it across all or most organizational units. However, when there is lack of agreement or divergence among individual-level perceptions of organizational climate within an organization (i.e., organizational-level climate), multi-modal distributions may emerge, corresponding to multiple subclimates rather than a random, uniform distribution of organizational climate (West et al., 2014). The relevant level of theory for subclimates is the group-level, whereby individuals are grouped into subgroup membership corresponding to the alignment or similarity of climate perceptions. Research has shown that subgroups may be formed according to individual characteristics such as organizational tenure, occupation, and job level (Chan, 2014).

Configural Measurement

The investigation of subclimates has received very little research attention in the climate literature. However, the perspective that climate can be patterned was leveraged by Roberson and Colquitt (2005) to propose a model of shared and configural climate whereby they specify that climate takes on specific configural forms when convergence of perception does not occur within work units. In particular, they defined configural climate as dissimilarities in member perceptions that are identified by the distribution of response patterns as either minimum/maximum or bi- or multi-modal. From their vantage point, configural forms of climate are viewed as indicative of nonconvergence of perception and are therefore likely to negatively affect team and organizational effectiveness since all group members do not share a common set of perceptions.

More recently, researchers have sought to expand the investigation of climate response patterns to examine climate configurations at the organizational level (Schulte et al., 2009; Ostroff & Schulte, 2014). There are several reasons for this. First, the identification of similar response patterns across the organization could reveal groupings of members that emerge with regard to characteristics such as age, gender, occupation, and education level, rather than by predetermined group membership. Second, response patterns could help to elucidate the degree to which these groups are aligned (Ostroff & Fulmer, 2014) with regard to the overall organizational climate, and could provide a rich diagnostic tool to differentiate groups when taking a multilevel perspective of climate.

Third, profiling response patterns could assist in the tailoring of practical interventions targeted to strengthening climate in specific groups (Zohar & Hofmann, 2012). The more holistic perspective of a configural compilation model lends itself to examining climate outside the traditional boundaries of work groups and departments and thus, would be more appropriate than dispersion composition models for identifying subclimates.

With regard to patterns of perception, research has suggested that configural measurement approaches can enable the examination of the manner in which groupings or patterns of similar responses occur when studying climate at the organizational level (Schulte et al., 2009). Configural approaches entail identifying patterns of variables or responses and grouping individuals or units with similar profiles together (Meyer, Tsui, & Hinings, 1993; Ostroff & Fulmer, 2014) into gestalts, typologies, modes, or archetypes. These groupings may be unobserved organizational subpopulations, defined as unobserved groups determined by specific configurations or patterns of variables (Owens & Schoenfeldt, 1979) that do not necessarily correspond to the boundaries of a formal work team or department. By using configural techniques to categorize or type people into attribute profiles, researchers have attempted to determine how subgroup membership may help to explain relationships and effects of unobserved heterogeneity on organizationally-relevant processes and behaviors (Dumenci, 2011). Configural approaches have been frequently used in organizational culture research to develop and test typologies and taxonomies by examining patterns across dimensions (Payne, 2006; Schein, 2010).

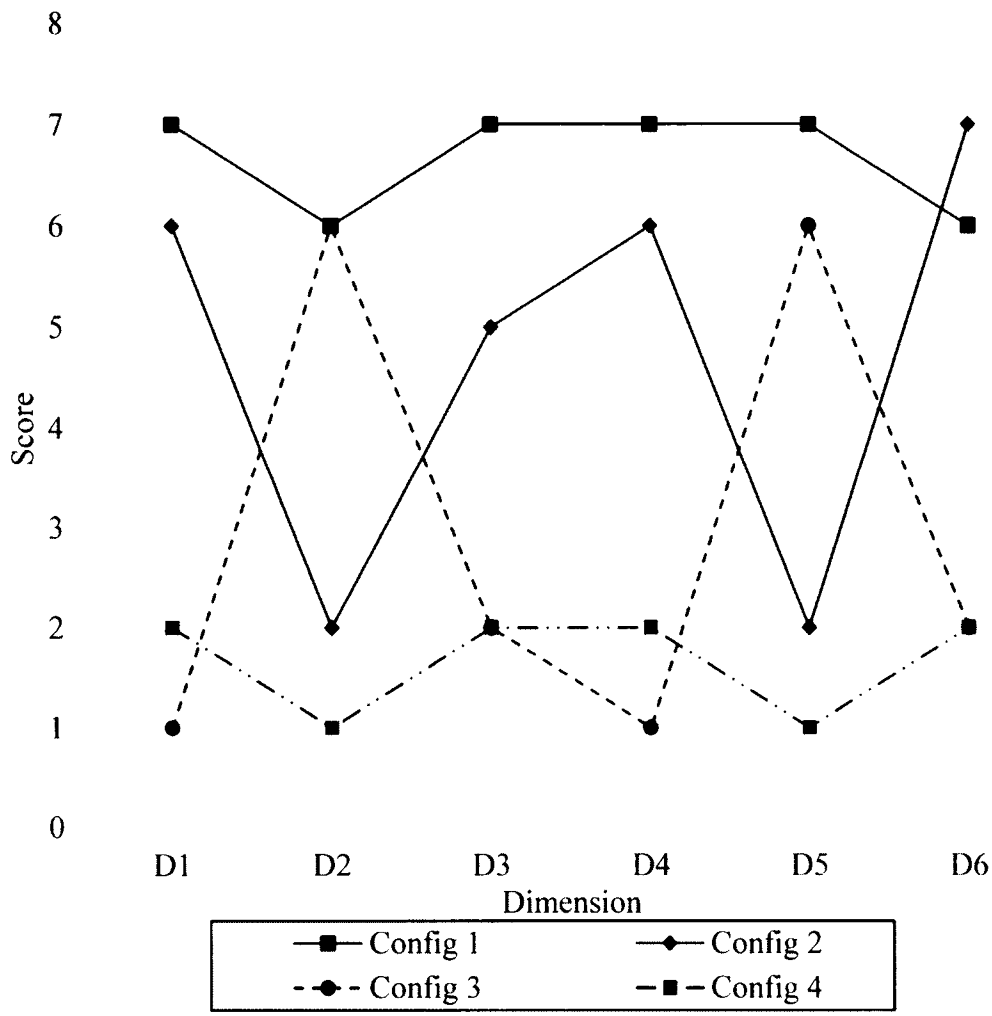

Figure 1. Hypothetical configural analysis, adapted from Ostroff and Schulte (2014), (pp. 534)

Figure 1 depicts a hypothetical configural analysis whereby the x-axis represents dimensions of climate and the y-axis the mean scores on the dimensions. Individuals or units (e.g., group or organization) with similar patterns of response are grouped together. In this example, individuals in configuration 1 have high scores across all dimensions, whereas individuals in configuration 4 have low scores across all dimensions. Configurations 2 and 3 exhibit variability in scores across the dimensions, but reveal opposing patterns of response. Research on climate has most often been undertaken with an aggregate approach, whereby subdimensions of a strategic facet (e.g., safety climate) are algebraically combined. To control for linear interrelationships among climate dimensions, climate researchers typically link outcomes of interest using multivariate procedures such as multiple regression (Ostroff, Kinicki, & Muhammad (2013). By doing so, a researcher may therefore determine which climate dimension is most important for a particular outcome of interest. An implicit assumption with regression-based tests is that a construct's dimensions' effects are independent and additive. However, multivariate tests do not account for interactions or non-linear relationships among dimensions, which have been shown to occur (Ostroff et al., 2003; Schulte, Ostroff, & Kinicki, 2006). In contrast, configural approaches allow for the examination of multiple dimensions or aspects of an organization simultaneously to define the climate construct, rather utilizing an additive combination. In this way, researchers may consider the interplay of dimensions or aspects while maintaining an overall view of the organizational context (Johns, 2006) allowing for the consideration of the social structure of climate (Schneider & Reichers, 1983). By examining the patterns of high and low values across climate dimensions and levels (see Figure 1), these approaches allow for a holistic perspective on the role each dimension plays in the organizational system. Researchers can then better understand if certain combinations of climate dimensions might better capture the entirety of the organizational context. Further, organizational climate researchers may account for the interdependencies and interactions of group profiles to determine their relative importance for success in achieving organizational outcomes (Tsui, Wang, & Xin, 2006).

From a climate perspective, configural approaches can help to explain how certain combinations of climate dimensions may better capture the multidimensional nature of the construct (Ostroff et al., 2013; Schneider et al., 2011; Zohar & Hofmann, 2012). With regard to subclimate identification, a configural approach offers the ability to represent organizational climate by classifying individuals into groups based on patterns of profile similarities across dimensions or variables, rather than grouped by predetermined collective memberships (Doty, Glick, & Huber, 1993). When considering climate emergence from the perspective of social comparison theory (Festinger, 1954) and homophily, configural approaches could help to explain how specific groups of employees may operate as a vehicle to transmit and maintain organizational climate (Schulte et al., 2009). It may also be possible to develop a theoretical typology of organizational climate similar to what has been attempted in the organizational culture literature (Patterson et al., 2005). Finally, and perhaps more fundamentally, the use of configural approaches would be a measurement approach consistent with acknowledgement of Schneider and Reichers' (1983) foundational work on the etiology of organizational climate that argued that structural characteristics of organizations, the types of people within organizations, socialization practices, and patterns of interaction and perception all play an important role in climate development and emergence and should therefore all be accounted for in climate research.

Analytical Approaches to Configural Analysis

Two analytical approaches, inductive and deductive, are used to determine patterns present in organizational data. The two approaches are similar in that they are used to classify an organization into smaller group categories (Wolfe, 1970), and primarily differ by whether empirically (i.e., inductively) or theoretically (i.e., deductively) derived (Ketchen, Thomas, & Snow, 1993). Inductive approaches, as the name suggests, entail analyzing data to determine configurations based on similarity of profile characteristics (e.g., response patterns). The resulting configurations are then labeled and interpreted before being examined in relation to outcomes of interest. Conversely, deductive approaches entail developing configurations a priori, based on a theoretically justified model. The data is subsequently examined against the model to determine whether the configurations deviate. Given that little work has been done to establish organizational climate typologies, a priori groupings are difficult to specify. Thus, inductive configural approaches are considered a more sensible application to determine the configurations present in organizational climate data (Schulte et al., 2009).

Cluster analysis (Aldenderfer & Blashfield, 1978; Everitt, Stahl, Leese, & Landau, 2011) and latent class modeling (Muthén, 2004; Nylund et al., 2007) are two configural approaches that have been most frequently used in organizational climate research. Both techniques have been suggested to be particularly useful for climate studies, as they both deal with profiling multiple, rather than single, variables and thus can accommodate the multidimensional nature of the climate construct (Ostroff & Schulte, 2014). Both approaches have advantages and disadvantages that must be weighed against the characteristics of the included variables (i.e., number, scaling, variability, and inter-correlations) before determining which is most appropriate for use.

Cluster analysis. Cluster analysis can be defined as the classification of similar objects into groups, or clusters, where the number of clusters and cluster parameters (e.g., means, variances, and covariances) are unknown (Aldenderfer & Blashfield, 1978; Kaufman & Rousseeuw, 2009). Within the context of organizational climate, cluster analysis is a procedure that can be used to sort observations (e.g., individuals) with similar climate scores across multiple variables into clusters (e.g., groups). Cluster analysis has been used in climate research to identify subgroups of employees who perceive the organization similarly. For example, using response profiles to climate surveys, González-Romá, Peiró, Lloret, and Zornoza (1999) and Patterson et al., (1996) related configural groupings (e.g., clusters) to collective climate membership and job type.

González-Romá and colleagues (1999) tested whether membership in collective climates was related to membership in collectives defined by departmental membership, hierarchical level, shift, job location, and organizational tenure. Their findings revealed that only hierarchical climates (i.e., top managers versus middle-to low-level employees) were significantly related to collective membership, suggesting that collective climates have psychosocial meaning based on the penetration of the top managers' views through other hierarchical levels. That is, the relationship between collective climate and hierarchical level revealed the scope of the top managers' view by revealing two distinct views of the organization. One view was held by top managers and the other by middle- to low-level employees. Although this study concluded that the validity of collective climates received partial support, the results did suggest that hierarchical level may be a factor in the formation of organizational climates. Further, this study established that clustering techniques may be a helpful exploratory tool when investigating organizational climate.

An advantage of cluster analysis is that since it is not based on a statistical model, it does not require assumptions about the distribution of data. A disadvantage is that researchers must make decisions regarding the clustering technique to be used in the analysis (e.g., hierarchical, k-means, Ward's method), as different techniques can yield very different results. An additional disadvantage is that the solutions generated by cluster analysis are not the most defensible, from a statistical point of view, when scale-variant variables must be included in the analysis (Vermunt & Magidson, 2002). In such cases where the characteristics of the included variables, (e.g., scaling variability, inter-correlations) could cause issues, latent class cluster analysis (LCCA) is a preferable technique (Ostroff & Schulte, 2014).

Latent class cluster analysis (LCCA). Latent class cluster analysis (Gibson, 1959; Lazarsfeld, Henry, & Anderson, 1968) is a model-based statistical approach whereby observations are assumed to belong to a latent class, with the number of classes and their size unknown a priori (Clogg, 1995). A latent class may be defined as an unobserved class that is similar with regard to observed variables (Vermunt & Magidson, 2000). Within the context of organizations, a latent class can be considered an unobserved subpopulation. Unobserved subpopulations can be defined as unobserved groups determined by specific configurations or patterns of variables (Owens & Schoenfeldt, 1979). By using configurations to categorize or type people into profiles based on patterns of response, researchers have attempted to explain how subpopulation membership may help to explain relationships and effects of unobserved heterogeneity on organizationally-relevant processes and behaviors (Dumenci, 2011). Within the context of organizational climate, latent, unobserved subpopulations are conceptually similar to subclimates. To explain how LCCA could be used to identify subclimates, it is helpful to understand the assumptions and advantages of this configural measurement approach.

With LCCA, observed scores are assumed to derive from the same probability distributions whose parameters have yet to be estimated. An important assumption of LCCA is that there are a certain number of unobserved, categorical classes that account for interrelationships among variables (Clogg, 1995). Hence, LCCA offers a probabilistic classifying approach that involves the estimation of two parameters: (a) the probability of a particular response for an observed variable, conditional on latent class membership, and (b) the probability of belonging to a specific latent class. Estimation of these parameters is typically carried out using the maximum likelihood (ML) estimation procedure in specialized software packages (e.g., Latent Gold™, Mplus™).

LCCA assumes that each individual belongs to a class, but uncertainty regarding individual class membership is taken into account. That is, observations are assumed to have a probability of membership for each cluster, and are therefore not assigned a priori to any one cluster. Applications of LCCA are most frequently exploratory in nature, whereby no a priori hypotheses regarding the nature of the latent classes are tested (Laudy, Boom, & Hoijtink, 2005). When conducting an exploratory LCCA, no explicit theories about underlying groups are attempted. Rather, the data are allowed to suggest the number and nature of groups. Posterior probabilities for class memberships for each individual are computed using both the a) estimated model parameters; and b) observed scores in latent class procedures. Importantly, after the latent class model is established, it is possible to classify other individuals belonging to the population based on their observed scores. This is not possible with cluster analysis.

The assessment of fit for latent class models may be carried out using a variety of statistical tools and hypothesis testing approaches (Nylund et al., 2007) When conducting an LCCA, a researcher must first specify a range of clusters before comparing the resulting latent class solutions with applicable model fit statistics to determine the most appropriate number of clusters for the final class solution (Finch & Bronk, 2011; Vermunt & Magidson, 2002). The Bayesian information criterion (BIC), adjusted Bayesian information criterion (aBIC), and Akaike information criterion (AIK), are all used for this purpose. Whichever criteria used, the model with the lowest criterion values offers the optimal solution and therefore informs the researcher of the most appropriate number of clusters. The BIC and aBIC are often considered most robust in terms of sample size and are thus frequently preferred (Ostroff & Schulte, 2014). In addition to information criterion, several hypothesis testing models can be used to assess LCCA model fit. These include the chi-square based likelihood ratio test (LRT), the Lo-Mendell-Rubin (LMR) test (Lo et al., 2001), and the parametric bootstrap likelihood ratio test (BLRT) (Nylund et al., 2007). There are restrictions on the appropriateness of use of these tests that should be taken into account based on the differing number of latent classes when comparing multiple models. The LMR is most appropriate test for comparing models with differing numbers of classes because it relies on an approximation of the chi-square distribution to obtain appropriate p-values for the difference in model likelihood (Finch & Bronk, 2011).

In summary, LCCA offers many advantages over cluster analysis (e.g., hierarchical and partitioning methods) when conducting organizational climate research. First, LCCA is a model-based approach. As such, it generates less arbitrary and more valid criteria for assessing and selecting a cluster solution. After a model is estimated for the population from which the sample being studied is taken (Vermunt & Magidson, 2002), the maximum likelihood method (MLM) is used to estimate the model parameters. Similar to structural equation modeling, the identification of the latent mixture involves maximizing a log-likelihood function, which generates a statistically consistent criterion (e.g., BIC) for allocating individuals to the latent clusters. In contrast, cluster analysis uses more arbitrary cluster allocation criteria. Typically, this involves minimizing the within-cluster variation and/or maximizing the between-cluster variation with regard to certain variables that are deemed important by the researcher. Second, LCCA has more formal information criteria and hypothesis tests available for making decisions about the number of latent classes and other model parameters, including how well a given model fits the observed data (Finch & Bronk, 2011). Third, because LCCA is model-based, it may be used in both confirmatory and exploratory applications. (Wang & Hanges, 2011). Fourth, LCCA is very flexible with regard to data, and both simple and complicated distributional forms may be used for observed variables within clusters. That is, if variables have normal distributions but unknown variances, the latent class estimations will be the same irrespective of whether the variables are normalized (Vermunt & Magidson, 2002). In a related vein, LCCA is scale invariant requiring no normalization of data. Therefore, mixed mode data can be used simultaneously, unlike cluster analysis (Bacher, 2000). These are all clear advantages of the use of LCCA over traditional cluster analysis techniques when examining organizational climate (Ostroff et al., 2013).

Characteristics of Configurations

Although the use of LCCA would theoretically allow for the classification of organizational climate into subclimates, based on the identification of groups exhibiting similarities in patterns of response, visual inspection of subclimate configurations are recommended to help better understand their distinct characteristics and to ascertain their relative importance to any outcomes of interest (Ostroff & Schulte, 2014). Three distinct profile characteristics are used for this purpose (Cronbach & Gleser, 1953; Nunnally, Bernstein, & Berge, 1995; Tabachnick & Fidell, 1989). Elevation, which is conceptualized as the mean level, is operationalized by the calculation of mean scores across all variables or dimensions within a group or organization. Variability, or scatter, is simply the variability across the variables or dimensions as calculated for a group or organization. Finally, shape represents the distinctive pattern of highs and lows or ups and downs across all variables or dimensions. The shape of a configuration is represented by dummy variables based on the configurations that emerge from an LCCA.

It is important to consider the characteristics of configurations when looking beyond group classification in order to understand the relative importance of (a) whether having a high score on all dimensions (e.g., high climate level) or (b) the specific pattern of high and low scores on dimensions is most important. For example, when investigating cross-level relationships between climate and satisfaction Schulte and colleagues (2009) predicted that elevation and variability would be more important for internal, employee-based outcomes, while shape was predicted to be more important for externally focused outcomes. They found that elevation was indeed important for employee affect and intentions to quit whereas shape was important for customer service and financial outcomes. These findings support the idea that configuration characteristics are assumed to be differentially important depending on the nature of the outcome under investigation and should thus be considered when conducting configural climate studies.

Safety Climate

Returning for a moment to the propositions of Kozlowski and Klein (2000) and Ostroff and Fulmer (2014) that variability in climate perceptions may be systematically patterned rather than random, few studies have examined organizational-level data for patterns of either convergence or divergence of climate perceptions between groups. A notable exception is the work of Zohar and Luria (2005) on between-unit dispersion of safety climate. Briefly, safety climate may be defined as perceptions shared among employees regarding organizational policies, procedures, and practices as they relate to the value and priority of safety within an organization as well as the related behaviors that get rewarded and supported (Zohar, 1980, 2000). In an effort to increase workplace safety and improve organizational safety performance, climate scholars have frequently investigated the role of safety climate as a predictor of safety behavior and safety-related outcomes (Christian, Bradley, Wallace, & Burke, 2009; Clarke, 2013; Glendon & Litherland, 2001; Hofmann & Stetzer, 1998). The predictive validity of safety climate as a robust indicator or predictor of safety outcomes has been widely demonstrated (Clarke, 2006; Zohar, 2010). For example, researchers have demonstrated negative associations with workplace accidents and injuries (Hofmann & Stetzer, 1996; Probst, 2004) and positive associations with safety behavior and safety compliance (Clarke, 2006; Nahrgang, Morgeson, & Hofmann, 2007) across settings, industries, and cultures. Four metaanalyses (Beus, Payne, Bergman, & Arthur, Jr., 2010; Christian et al., 2009; Clarke, 2010; Nahrgang, Morgeson, & Hofmann, 2011) examined a total of 202 studies and found strong, robust relationships between safety climate and subjective and objective safety outcomes. However, key theoretical questions remain regarding the conditions under which safety climate perceptions diverge (Zohar, 2010; Zohar & Hofmann, 2012). Further, there is a dearth of studies that examine organization and subunit safety climates simultaneously (Zohar, 2010). Given that organizations are characterized as complex social systems (Katz & Kahn, 1978) that exhibit interdependence between individuals and subunits across the organizational hierarchy (Kozlowski & Klein, 2000), additional studies are needed to investigate cross-level relationships and between-group dispersion in safety climate (Zohar, 2003, 2010).

Between-Units Dispersion

To address these questions, Zohar and Luria (2005) developed and tested a between-units dispersion model of safety climate and introduced a new construct called climate variability. Climate variability is an organizational-level variable that operationalizes the between-group variance of group climate levels in individual organizations. Based on Chan's (1998) dispersion model, which suggests that perceptual variability among group members is meaningful, Zohar and Luria argued that the variation in climate levels between groups is non-random and therefore, meaningful. Theoretically, the authors argued that increasing organizational climate strength not only induces stronger group-level climates, but also reduces variability of climate perceptions between groups. More specifically, the authors argued that organizational- and group-level climates would be aligned and that organizational climate strength would be negatively related to climate variability (e.g., variability between groups). The authors found support for both global alignment between levels and the hypothesis that organizational climate strength was negatively related to between-groups variability. Further, they found that organizational safety climate strength was related to safety climate convergence between units. However, their climate variability data showed significant variance, which implied cross-level discrepancies. The authors suggested that discrepant group climates, defined by deviating from organizational climate by 1.0 SD units or more, should be further examined to understand the dynamics of cross-level relationships.

What is important about Zohar and Luria's (2005) between-units dispersion model is that it recognizes the need to examine the variability of climate perceptions at the organizational level by examining between-groups variability, and to investigate whether climate strength is globally aligned between the organizational- and group-levels. However, they used formalized work units as groups in their dispersion model, which could have masked important response patterns at the organizational level. Returning to the frameworks supported by the differentiation perspective of organizational climate, the view that variability in organizational climate perceptions may be patterned, and related to functional and occupational differences rather than level, should be considered when investigating safety climate. In the case of extending a between-units dispersion model of safety climate, this argument would support the reconceptualization of groups as subclimates, rather than work teams, departments, or branches.

Research Questions and Hypotheses

The preceding review shows that a growing body of research indicates that both within-group agreement as well as between-group variability of organizational climate perceptions may provide unique insight into understanding differential group functioning and climate effects in organizations (Ehrhart et al., 2013). Using configural approaches such as LCCA may provide increased insight in this area of safety climate research, particularly since this approach allows for the exploratory analysis of organizational climate data outside the confines of traditional work group boundaries (Wang & Hanges, 2011). Further, the use of LCCA to investigate safety subclimates allows for a new conceptualization of Zohar and Luria's (2005) between-units dispersion model by explaining between-units safety climate dispersion using Fulmer & Ostroff's (2015) patterned emergence compilation argument as a framework for investigating variability between subclimates instead of work groups.

To facilitate the investigation of these issues, the following research questions were posed:

1. Will LCCA yield a model that has an acceptable fit to organizational safety climate data?
2. Can safety subclimates be identified based on identifiable patterns of response along the dimensions of the Organizational Safety Climate Scale (OLSC; Zohar & Luria, 2005)?
3. What are the respective profile characteristics for each subclimate?

4. Given that research has shown that subclimates may be formed according to individual characteristics such as organizational tenure, occupation, and job level (Chan, 2014; West et al., 2014), are the subclimates meaningful in terms of homogeneity of demographic attributes?

In addition to the preceding research questions, the following hypotheses were also posed:

1. The 3-factor structure of Zohar and Luria (2005) for the OLSC will be replicated.
2. Subclimates will differ based on the profile characteristics of elevation, shape, and variability.

CHAPTER 2

METHOD

To examine the research questions and hypotheses, an archival dataset containing demographics and organizational safety climate data was used. The data were gathered in 2014 as part of a cross-sectional survey effort to support strategic planning and budgetary decisions for safety training and safety data management systems. The organization from which the data were gathered is a large, multi-national corporation with approximately 85,000 employees and operations in more than 100 countries. In addition to the organization's operations being geographically dispersed, operations span multiple lines of business across several safety-critical industries. The organization granted permission for the use and publication of the data for research purposes. A data security plan was provided at the organization's request, which assured that all data would be protected, de-identified prior to publication, and reported only at aggregated, grouped levels.

Participants

Invitations to participate in the survey were sent via an internal electronic mailing list that contained a cross-section of approximately 8,000 employees. The subscribers to the list were representative in terms of demographics, with subscribers being comprised of executive management, supervisory, and non-supervisory employees across all lines of business and all countries with active operations. Participation was strictly voluntary, and every person receiving an invitation was given the opportunity to opt out of participating. All respondents were assured their responses would be confidential.

Procedure

The survey was web-based and administered in English. The use of English was deemed appropriate, as this is the official operating language of the organization. Each participant received, via company email, a survey invitation with a unique link. The completion of an informed consent form was required in order to participate. The survey was active for a two-week period, during which one follow-up reminder was sent to any non-responders, except those who had opted out of participating in the survey.

For the purposes of this study, subclimates were conceptualized as latent, unobserved groups who exhibit high climate strength and significant between-group variation in climate perceptions. Given the empirically-driven nature of an exploratory LCCA, and lack of available climate typologies, no specific a priori hypotheses were proposed regarding the subclimates (Laudy et al., 2005). Rather, the data were allowed to suggest the number and nature of subclimates. Elevation, variability, and shape (Cronbach & Gleser, 1953; Nunnally et al., 1995; Tabachnick & Fidell, 1989) were the profile characteristics examined for this study. Elevation, was conceptualized as the mean level of climate perceptions, and was operationalized by the calculation of mean scores across all OLSC dimensions within a subclimate. Similarly, variability was calculated across all OLSC dimensions for each subclimate. Shape was represented by the distinctive pattern of highs and lows across the OLSC dimensions for each subclimate.

Measures

All measures were self-report. Survey participants completed the Organizational-Level Safety Climate (OLSC) scale (Zohar & Luria, 2005). Permission was obtained by the authors for use of the OLSC (see Appendix A). The survey contained 15 OLSC items (see Appendix B) accompanied by a 5-point Likert (Likert, 1967) rating scale, ranging from 1 (completely disagree) to 5 (completely agree). When averaged, the scale score provides the organizational climate level measurement parameter (i.e., mean climate score) for a focal group (e.g., organization or subunit). In addition to the OLSC items, survey participants answered several demographic items as well (Appendix B).

OLSC Dimensionality and Factor Structure

By Zohar's (2010) own assessment, review articles have identified many empirically tested safety climate scales (Flin, Mearns, O'Connor, & Bryden, 2000) that cover more than 50 different variables and conceptual themes (Guldenmund, 2000). Although there is wide agreement that organizational safety climate is hierarchical in structure, with a global, higher order factor (Griffin & Neal, 2000), there is disagreement over the number and nature of the first-order factors (e.g., social standing, worker involvement, competence level, safety knowledge, communication flow, status of safety issues; see review in Flin et al., 2000). Regarding the global factor, research has shown that management commitment to safety is consistently identified as a major dimension of safety climate (Brown & Holmes, 1986; Coyle, Sleeman, & Adams, 1995; Dedobbeleer & Béland, 1991; Zohar, 1980) and that the use of this global factor can simplify the study of safety climate in models that contain many other variables (Christian et al., 2009; Hofmann & Stetzer, 1996; Wallace & Chen, 2006).

The OLSC scale items include a range of indicators that reflect either (a) top management's commitment to safety or (b) the priority of safety over competing operational goals such as production speed and costs. Previous exploratory factor analysis by Zohar and Luria (2005) on the level-adjusted (e.g., organizational- and group-level) OLSC scales yielded three rotated factors identified as Active Practices (Monitoring–Enforcement), Proactive Practices (Learning–Development), and Declarative Practices (Declaring–Informing) and whose scores were calculated by averaging related indicators. Across exploratory (Brown & Holmes, 1986; Dedobbeleer & Béland, 1991; Zohar, 1980) and confirmatory (Mueller, DaSilva, Townsend, & Tetrick, 1999) factor analyses, two-, three-, four-, and eight-factor solutions have been reported for the OLSC. Zohar and Luria have confirmed that substantial item cross-loadings and high intercorrelations among OLSC factor scores does indeed suggest a global factor relating to managerial commitment, resembling that reported by Griffin and Neal (2000). Since then, both the three-factor structure and single higher-order factor structure have been replicated by Johnson (2007), lending support and psychometric documentation for both solutions for the OLSC. However, due to the high intercorrelations among OLSC factor scores found by Griffin and Neal, Zohar and Luria suggested that researchers examine the underlying factor structure when using the scale. Thus, a confirmatory factor analysis (CFA) was indicated to determine how well the hypothesized three-factor model fit the sample data.

Confirming the Factor Structure of the OLSC via CFA

A CFA is used to postulate, based on knowledge of an underlying latent variable structure, relations between the observed measures and underlying factors (Brown, 2006). The model is thus specified *a* priori and the hypothesized structure is tested statistically to determine its fit to sample data. Given recent commentary regarding a lack of standardization in CFA reporting (Kline, 2015), the reporting guidelines of Jackson, Gillaspy, and Purc-Stephenson (2009) serve as a valuable framework to ensure related data preparation, analysis decisions, model evaluation, modifications, and findings were reported in a manner consistent with previously established recommendations (Boomsma, 2000; Hoyle & Panter, 1995; McDonald & Ho, 2002).

Prior to undertaking a CFA, researchers must first assess data integrity. Importantly, the evaluation of distributional assumptions of various CFA model estimation methods requires that certain multivariate assumptions be considered and assessed before determining the most appropriate method for proceeding with the analysis (Curran, West, & Finch, 1996; Kline, 2015). Two assumptions of multivariate statistics are that the (a) variance/covariance matrices across *k* groups must be homogenous and (b) the interval response variables across *k* groups must be multivariate normally distributed (Burdenski, 2000). With regard to CFA, these assumptions are not only important to establish for reasons related to model specification, but also for subsequent estimation and evaluation of the model(s) being tested. For example, models estimated via the frequently used maximum likelihood (ML) require the establishment of multivariate normality in order to avoid overestimations of the chi-square (X^2) statistic, related Type 1 error (Schafer & Graham, 2002), and downward-biased standard errors

(Kaplan, 2000). Further, a lack of multivariate normality may undermine assumptions of ancillary fit measures critical for interpreting the results of a CFA estimated via ML (Yuan, 2005).

In addition to the assessment of multivariate normality, the nature and extent of missing data must also be assessed. The method used to treat missing data (e.g., listwise deletion, pairwise deletion, mean substitution, multiple imputation, or expectation minimization) can affect subsequent findings. For example, research has shown that parameter estimates may be biased and convergence failures may become more likely depending on the method employed (Enders & Bandalos, 2001). In general, listwise deletion of observations with missing data points has been found to be the most acceptable approach when data are missing at random (McKnight, McKnight, Sidani, & Figueredo, 2007; Schafer & Graham, 2002). Jackson and colleagues (2009) recommend that whichever method employed be expressly noted when reporting the results of a CFA.

Types of fit indices. Fit indices are summary statistics that evaluate how well a covariance measurement model explains sample data by (a) quantifying features of the hypothesized model and (b) providing information about the degree to which a given model is specified (Hu & Bentler, 1998). In particular, fit indices are metrics used to determine whether a latent variable model is acceptable for the sample data being analyzed. Researchers have distinguished between four major types of model fit indices that can be used as guidelines to determine whether the model being tested reflects, or fits, underlying theory (Marsh, Hau, Balla, & Grayson, 1998; Bentler, 1990). Absolute fit indices determine how well a model fits sample data (McDonald & Ho, 2002) and are derived from the fit between the obtained and implied covariance matrices, and the ML minimization function. Examples of this type of index include X2, the goodness-of-fit statistic (GFI), the adjusted goodness-of-fit statistic (AGFI), the root mean square error of approximation (RMSEA), the root mean square residual (RMR), and the standardized root mean square residual (SRMR). The X^2 index, in particular, forms the basis for many of the absolute fit indices and is traditionally used to evaluate overall model fit (Hu & Bentler, 1999). Often, X^2 is referred to as a 'badness of fit' (Kline, 2015) measure as a good model fit provides a nonsignificant result at the 0.05 threshold (Barrett, 2007).

Although X^2 remains a popular index for reporting CFA results, it does have limitations that should be considered by researchers. For example, multivariate normality is assumed. If sample data deviate from this assumption, it can appear that the model is rejected, even when it is properly specified (McIntosh, 2006). Further, X^2 is sensitive to sample size. When sample sizes are large, the statistic usually rejects the model (Bentler & Bonett, 1980). Under either of these circumstances X^2 may not be the best index to determine model fit. Importantly, other absolute fit indices, such as GFI, are derived from X^2 as simple transformations and may thus not necessarily provide non-redundant evaluation information (Tanaka, 1993). Even though absolute fit indices are known to be subject to these detrimental effects, they are routinely reported in covariance structure analysis.

Unlike absolute fit indices, incremental fit indices such as Bollen's Incremental Fit Index (IFI), the Bentler-Bonett Normed Fit Index (NFI), the Tucker-Lewis Index (TLI), and the Comparative Fit Index (CFI) compare X^2 for the model being tested (i.e., alternative) to a baseline independence (i.e., null) model that specifies that all observed variables are uncorrelated. Basically, these indices are computed by using ratios of the two models taking their degrees of freedom into account. The IFI and NFI are sensitive to small sample sizes, and tend to underestimate fit when samples are less than 200 (Bentler, 1990). Of the incremental fit indices, the TLI, which is also known as the non-normed NFI, is preferred for large samples (Kline, 2015; Tabachnick & Fidell, 2007). Additionally, the CFI is one of the most popular and widely reported fit indices due to being little affected by sample size (Fan, Thompson, & Wang, 1999).

Parsimonious fit indices (e.g., PGFI, PCFI, BIC, AIC), so named because they penalize models with greater complexity, are infrequently used for fit evaluation (Crowley & Fan, 1997). Rather, these indices are more frequently useful for evaluating alternative theories favoring parsimony. That is, if a simpler alternative model is identified as exhibiting good fit, these indices can assist researchers in determining whether to favor those simpler models over more saturated, complex models. Mulaik and colleagues (1989) strongly suggest that these indices be used in tandem with other goodness of fit measures, particularly because firm threshold levels have not been established and this can make interpretation very difficult.

A related and important point is that some fit indices are differentially sensitive to types of model misspecification (Hu & Bentler, 1998, 1999). For example, X^2 can be problematic in terms of usefulness for evaluating model fit not only because it is affected by large sample sizes, but also because it is affected by model size and the distribution of variables (Brown, 2006). Brown (2006) stipulates that TLI, CFI, and RMSEA have all been found to be sensitive when factor loadings are misspecified, and SRMR when factor covariances are misspecified. Hu and Bentler (1998) and Kline (2015) suggest that due to these types of issues, the optimal approach is to rely on several fit indices that have different measurement properties such as an incremental fit index like CFI in conjunction with a residuals-based index such as the SRMR. In general, the RMSEA, the TLI, and the CFI have all been found to perform well with regard to detecting model misspecifications and are relatively unaffected by sample size (Hu & Bentler, 1998; Marsh, Hau, Balla, & Grayson, 1998) and are thus a frequently preferred basis for determining model fit (Hooper, Coughlan, & Mullen, 2008).

Cutoff values for fit indices. Much like the choice of indices to be used for model fit evaluation, the choice and use of their respective cutoff values may be somewhat subjective. Contradictory recommendations exist within the literature with regard to the standards that should be used (Yuan, 2005), but researchers have generally agreed that cutoff values should be explicitly stated for any index used and that aspects other than of model fit should be holistically examined as well (Jackson et al., 2009). By doing so, the examination of standardized residuals and parameter estimates may help to ensure relationships and anticipated signs and magnitudes are both accounted for and in alignment with research expectations and may lend additional substantiation to interpretation of findings (Boomsma, 2000). Table 2 presents an overview of common fit indices, their acceptable threshold levels, and a brief description of applicable considerations.

Table 2

Fit Indices and Acceptable Thresholds

Fit Index	Threshold Level	Considerations for Use
X^2	Low X^2 relative to the *df* with a nonsignificant *p* value ($p > .05$)	
RMSEA	Values < .07 (Steiger, 2007)	Known distribution. Favors parsimony. Values < .03 represent excellent fit.
GFI	Values > .95	Scaled between 0 and 1. Higher values indicate better model fit. Use with caution.
AGFI	Values > .95	Adjusts GFI based on model parameters. Values can fall outside the 0 to 1 range.
RMR	Good models have small RMR (Tabachnick & Fidell, 2007)	Residuals-based index. Unstandardized. Represents average squared differences between the residuals of the sample and estimated covariances.
SRMR	Values < .08 (Hu & Bentler, 1999)	Standardized version of RMR. Easier to interpret.
NFI	Values > .95	Assesses fit relative to baseline model with no covariances assumed between observed variables. Tendency to overestimate fit in small samples.
NNFI (TLI)	Values > .95	Non-normed. Values can fall outside 0 to 1 range. Favors parsimony. Performs well across distributions and sample sizes (McDonald & Marsh, 1990)
CFI	Values >.95	Normed. 0 to 1 range.

Note. RMSEA = root mean square error of approximation, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, RMR = root mean residual, SRMR = standardized root mean residual, NFI = normed fit index, NNFI (TLI) = non-normed fit index (Tucker-Lewis index), CFI = comparative fit index.

CHAPTER 3

RESULTS

Prior to conducting the analyses addressing hypotheses and research questions, a series of preliminary analyses were performed to screen the data for missing cases and to ensure that the univariate and multivariate assumptions underpinning CFA and LCCA were fulfilled.

Data Integrity: Multivariate Normality and Missing Data

Given the recommendations of Jackson and colleagues (2009), several steps were taken to screen and prepare the data prior to conducting the CFA for this study. First, an analysis of missing data was conducted. Observations with missing data were determined to be random and were deleted using the listwise procedure (McKnight et al., 2007). Second, univariate and multivariate skewness and kurtosis were examined. DeCarlo (1997) notes that while skewness is known to affect tests of means, kurtosis is known to severely affect tests of variance and covariance. As such, researchers engaged in conducting CFA are strongly encouraged to pay particular attention to kurtosis values (Byrne, 2016).

Mardia's (1970, 1974) multivariate kurtosis coefficient was calculated and the normalized estimate was examined as an index of multivariate kurtosis. As a guideline, Bentler (2005) suggests that rescaled β_2 values of greater than 5 are suggestive of non-normality. In the case of this study, the tests indicated that while univariate skewness and kurtosis and multivariate skewness were not problematic (Cohen, Cohen, West, & Aiken, 2013), the data did exhibit evidence of multivariate kurtosis with a Mardia's value of 18.23 (p = .000). To address this issue, outliers were identified using the Mahanobis Distance (D^2) procedure, and 82 cases were removed based on the corresponding chi square critical values. Subsequent reexamination on the data then showed that multivariate kurtosis was acceptable (DeCarlo, 1997) and that further analysis could proceed. Finally, the remaining data were found to meet the assumption of homogeneity of variance as outlined by Tabachnick and Fidell (1989, 2007). A non-significant Box's M (Box, 1949, 1954) test (M = 12.89, p =.394), indicated homogeneity of covariance matrices based on Huberty and Petoskey's (2000) guidelines. Thus, both conditions put forth by Burdenski (2000) for multivariate analysis were met. No data manipulation procedures, such as transformations, were used.

Descriptive Statistics of Final Sample and OLSC

The data preparation and screening procedures resulted in a final sample size of 1089. More specifically, the original sample of 1369 was reduced by (a) 82 outlier cases that were identified and removed and (b) 198 cases that were removed due to missing data.

Table 3

Demographic Characteristics of Final Sample (N = 1,089)

Characteristic		*n*	%
Gender			
	Female	349	32
	Male	740	68
Age (years)			
	18-34	260	24
	35-54	671	62
	55-Over	158	14
Highest Level of Education			
	Secondary	237	22
	University	565	52
	Graduate	387	26
Organizational Tenure			
	<5 years	420	39
	6-15 years	413	38
	>16 years	256	23
Job Function			
	Non-Supervisory	227	21
	Middle Management	242	22
	Upper Management	620	57

As indicated in Table 3, the final sample was largely male (68%), and all organizational hierarchical levels were represented. Organizational tenure groups were designated as advanced if respondents had greater than 16 years of employment, moderate if 6 to 15 years, and low if less than 5 years. The respondents were highly educated, with 52% holding university-level degrees or related education and certifications, and a further 26% advanced graduate degrees.

Measures of internal consistency were calculated to estimate OLSC scale reliability. The results indicated that Cronbach's α for the scale was .95, which was well above the generally accepted minimum standard of .70 (Nunnally, 1978) and higher than the reliability estimate of .92 previously reported by Zohar and Luria (2005). In accordance with the recommendations of Zohar and Luria (2005), the intercorrelations of the OLSC items were examined and are presented in Table 4.

Table 4

OLSC Inter-item Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1.00														
2	.618	1.00													
3	.604	.707	1.00												
4	.526	.520	.619	1.00											
5	.570	.610	.642	.624	1.00										
6	.636	.568	.577	.565	.607	1.00									
7	.498	.562	.591	.482	.522	.535	1.00								
8	.496	.470	.534	.485	.561	.571	.578	1.00							
9	.544	.590	.640	.524	.586	.565	.571	.610	1.00						
10	.480	.563	.586	.544	.562	.576	.548	.543	.612	1.00					
11	.516	.542	.587	.509	.543	.563	.608	.555	.604	.603	1.00				
12	.566	.589	.606	.542	.566	.595	.577	.594	.629	.605	.658	1.00			
13	.553	.575	.617	.562	.614	.595	.587	.613	.615	.607	.669	.713	1.00		
14	.464	.540	.565	.422	.483	.481	.550	.487	.565	.610	.580	.579	.576	1.00	
15	.498	.544	.556	.532	.574	.556	.528	.567	.617	.623	.613	.636	.645	.640	1.00

Note. Numbers correspond to OLSC items 1 – 15.

Factor Structure of the OLSC

Hypothesis 1

Turning from data preparation procedures to testing, Hypothesis 1 hypothesized the three-factor structure of Zohar and Luria (2005) for the OLSC would be replicated. Regarding the need to clearly define and justify the model to be tested, the prior factor analytic work of Zohar and Luria provides the basis for the examination of the three-factor measurement model specified in Figure 2. Specifically, this model specification hypothesizes *a priori* that (a) responses to the OLSC could be explained by the three factors Active Practices (Monitoring-Enforcing [ME1]), Proactive Practices (Promoting Learning, Development [LD2]), and Declarative Practices (Declaring, Informing [DI3]) previously identified and defined by Zohar and Luria; (b) each observed item of the OLSC scale has a nonzero loading on the safety climate factor it was designed to measure; (c) the three factors (i.e., subscales) are correlated, and (d) the error terms associated with the item measurements are uncorrelated.

The use of the observed measures (OLSC 1-15) to identify the latent variables (ME1, LD2, DI3) in this model are justified, based on the validation studies by Zohar and Luria of the shortened, level-adjusted OLSC scales. As previously noted, two- three- four- and eight-factor solutions have all been reported for safety climate scales across exploratory (Brown & Holmes, 1986; Dedobbeleer & Béland, 1991; Zohar, 1980) and confirmatory (Mueller et al., 1999) factor analyses. However, the three-factor structure of the shortened, level-adjusted version of the OLSC has since been replicated by Johnson (2007), lending further support for the primary confirmatory evaluation of this particular factor model for the examination of the hypotheses and research questions of this dissertation.

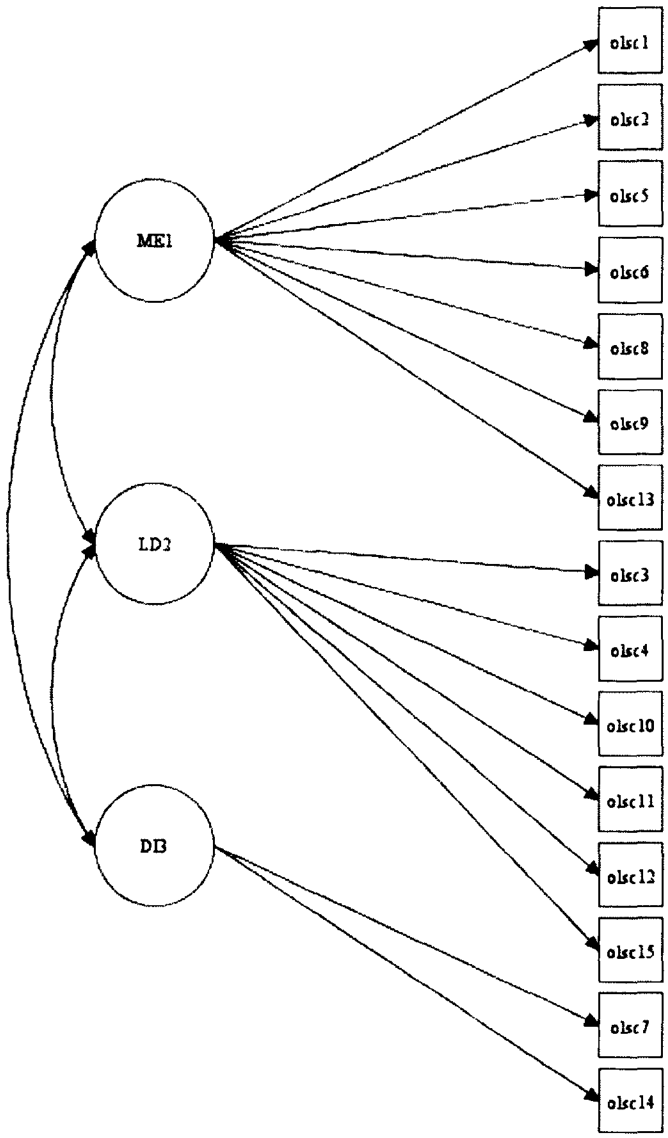

Figure 2. Three-factor measurement model for OLSC

Analytical Decisions

Although measures were taken during the data preparation phase to address non-normality of the sample data (i.e., removal of outliers and missing data), the data did not follow a multivariate normal distribution. Byrne (2016) suggests that, when analyzing data that are non-normal, researchers should consider the use of alternative approaches to traditional ML estimation methods. For example, the asymptotic distribution-free (ADF) method of estimation (Browne, 1984) has been suggested as a viable alternative for such circumstances. However, research has shown that the ADF method can yield severely distorted estimated values and standard errors (Hu, Bentler, & Kano, 1992; West, Finch, & Curran, 1995) and that it should only be used when sample sizes are extremely large (Raykov & Marcoulides, 2000).

Some authors recommend that when dealing with multivariate non-normal data, it is more appropriate to correct the ML test statistic rather than utilize an alternative estimation method (Chou, Bentler, & Satorra, 1991; Hu et al., 1992). In particular, the "Robust ML" estimation method is an alternative to the traditional ML estimation method that has proven advantageous for data that violate the assumptions of a multivariate normal distribution (Jackson et al., 2009). Importantly, although Robust ML methods provide the same estimates of model fit as ML (e.g., minimizing differences between matrix summaries of observed and estimated variances/covariances), the standard errors and chi-square generated by the Robust ML estimation are robust to non-normality of outcomes and non-independence of observations (Satorra & Bentler, 1994).

To support Robust ML estimation, Satorra and Bentler developed a statistic with a scaling correction for both the chi-square and estimated parameter standard errors that are produced via traditional ML estimation methods. Commonly referred to as the Satorra-Bentler chi-square (S-B X^2), this statistic has been shown to be reliable for evaluating measurement models under a wide variety of distributions and sample sizes (Curran et al., 1996) and is also considered the most straightforward strategy to use when assumptions of multivariate normality have been violated (Finney & DiStefano, 2006).

Thus, given that the data for this study exhibited evidence of multivariate kurtosis, the estimation method chosen for this CFA was Robust ML using the S-B X^2 statistic as a scaling correction.

CFA Results

Findings from the CFA measurement model are presented in Table 5. In accordance with the recommendations of Hu and Bentler (1999) to use several fit indices with different measurement properties when evaluating model fit, the following fit indices were used in this study: RMSEA (Steiger & Lind, 1980), CFI (Bentler, 1990), TLI (Tucker & Lewis, 1973), and SRMR (Hu & Bentler, 1999). Although both the X^2 and S-B X^2 were significant, this finding was not unexpected given the large size of the sample (Byrne, 2016). Determination of model fit was therefore based on the evaluation of the other fit indices, using the aforementioned cutoff values for the CFI, TLI, and SRMR indices.

Table 5

CFA Results Summary for the Three-factor OLSC Model

Model	Cronbach's α	X^2	S-B X^2	*RMSEA*	*CFI*	*TLI*	*SRMR*
Three-factor	0.951	564.211*	456.444*	0.071	.949	.938	.032

*p=.05, df=87
Note. *S-B X^2* = Satorra-Bentler chi-square, RMSEA = root mean-square error of approximation, CFI = comparative fit index, TLI = Tucker-Lewis index, SRMR = standardized root mean square.

As shown in the table, both the CFI and TLI values met or exceeded acceptable cutoff values (i.e., >.90). Further, the SRMR indicated acceptable model fit. As recommended by Boomsma (2000) and Thompson (2007), the standardized model parameter estimates were subsequently examined to ensure hypothesized relationships were in the expected directions and magnitudes. The standardized model parameter estimates, to include the variances of exogenous variables and their standard errors, are shown in Figure 3. Taken together, the results of the CFA and evaluation of the corresponding measurement model indicated acceptable fit of the hypothesized model and supported Zohar and Luria's (2005) three-factor structure for the OLSC. Hypothesis 1 was therefore supported.

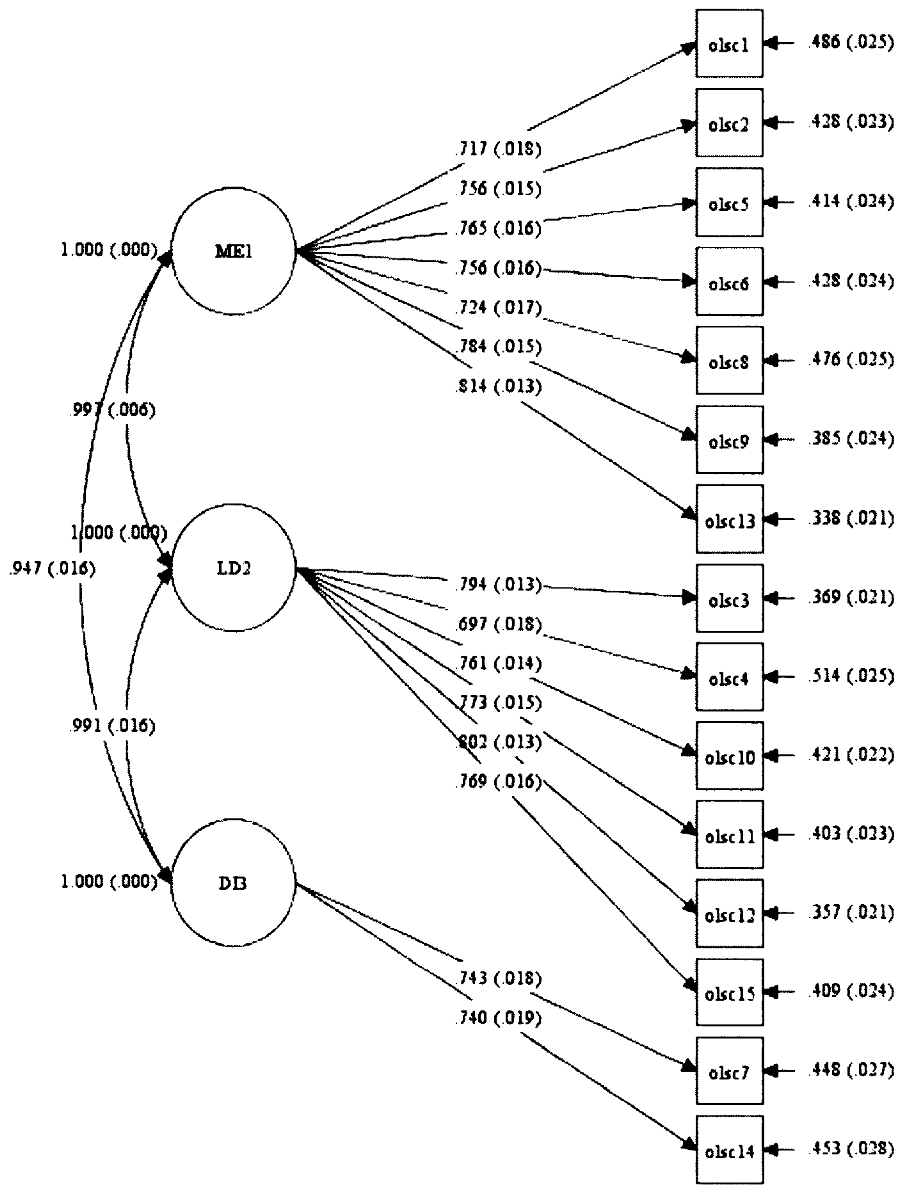

Figure 3. Standardized model parameter estimates for the CFA

Subclimate Identification Using LCCA

Research Questions 1 and 2

The first two research questions were interrelated. Research Question 1 concerned whether an LCCA would yield a model that has an acceptable fit to safety climate data. Research Question 2 was whether safety subclimates could be identified with LCCA based on patterns of response along the factors (i.e., dimensions) of the OLSC. Given that the hypothesized factor structure of the OLSC was supported, the sample data were subjected to LCCA using the three confirmed factors ME1, LD2, and DI3 as grouping variables. Specifically, a mixture model using a Robust ML estimator was used to identify safety subclimates within the final sample. Five separate models, ranging from two to six classes, were estimated. The final class counts for all estimated model solutions are presented in Table 6.

Table 6

Final Class Counts for Two- through Six-class LCCA Model Solutions

	2 Classes	3 Classes	4 Classes	5 Classes	6 Classes
	C1 = 846	C1 = 739	C1 = 665	C1 = 42	C1 = 93
	C2 = 243	C2 = 179	C2 = 228	C2 = 140	C2 = 35
		C3 = 171	C3 = 140	C3 = 188	C3 = 596
			C4 = 56	C4 = 61	C4 = 167
				C5 = 658	C5 = 120
					C6 = 78

Note. C = Class

Assessment of LCCA Model Solutions

In order to identify the appropriate number of classes, it was necessary to compare the two- through six-class models and select a final class solution based on both statistical and substantive grounds (Muthén, 2004). With regard to statistical assessment, Nylund et al. (2007) suggest that the Bayesian Information Criterion (BIC) value (Schwarz, 1978), a measure of model parsimony and fit, be used to compare class models. A secondary statistical method to compare class models is the use of entropy values, which range between 0.0 and 1.0. Entropy values are functions of the average posterior probabilities of class membership (Muthén & Muthén, 2000). These metrics provide information on whether individuals can be meaningfully assigned to a given class. Simply put, if an individual has a high probability of membership in a single class, denoted by a high entropy value above .80 and a low probability of membership in all other classes, they are said to be easily assigned. As shown in Figure 4, BIC values decreased until a fifth class was added, at which point the value became negative. In the case of the entropy values, Classes 3, 4, and 5 all have values above .80, and the quality of classification may therefore be deemed high (Muthén, 2004).

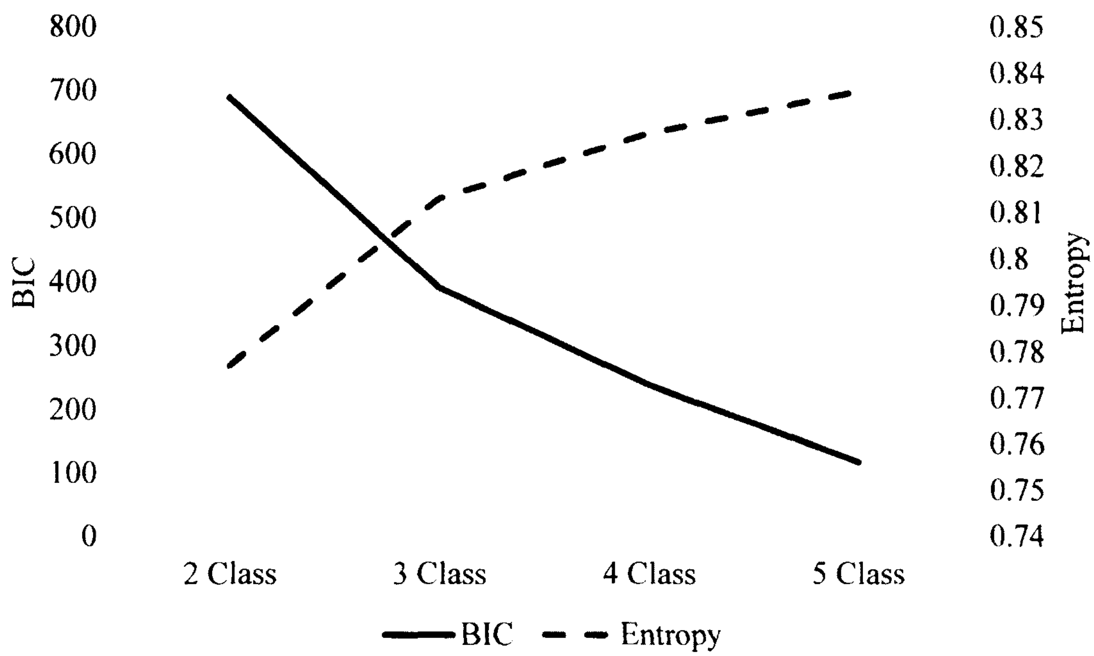

Figure 4. Model comparison of class solutions

When the drop in BIC values slows, Muthén (2004) suggests that the appropriate next step is to consider additional decision criteria based on substantive (i.e., non-quantitative) methods. One such method that may be used is to examine whether adding additional classes creates classes with very small numbers and hence, a potential loss of explanatory power. In the case of the present study, the four-class solution resulted in the smallest class including 56 respondents. The smallest classes in the five- and six-class solution, on the other hand, included 42 and 35 respondents, respectively. When using only substantive assessment criteria, it may seem unlikely that the small classes resulting from the four-, five-, and six-class solutions would provide relevant information regarding organizational-level safety subclimates. However, when class counts are viewed in concert with the BIC and entropy values, the relative decrease in BIC values corresponding to the addition of the five-class solution suggests a better fit to the data than the four-class solution. Further, the decline in BIC values attenuated with the addition of a sixth class, leading to a negative value (Table 7). Negative BIC values can indicate a loss of explanatory power from adding an additional class to the solution and are an indication to more closely examine and compare class solutions in relation to one another by using likelihood-based tests (Nylund et al., 2007).

Table 7

Two- through Six-class LCCA Model Comparison

	2 Classes	3 Classes	4 Classes	5 Classes	6 Classes
BIC	688.792	391.521	238.767	117.185	-15.939
Entropy	0.777	0.813	0.827	0.836	0.838
L-M-R LRT	2v1	3v2	4v3	5v4	6v5
	544.377 $p = 0.000$	314.017 $p = 0.000$	174.488 $p = 0.088$	144.392 $p = 0.629$	155.536 $p = .347$

Note. BIC = Bayesian Information Criterion, L-M-R LRT = Lo-Mendell-Rubin Likelihood Ratio Test

A closer examination and comparison of the class solutions were conducted using the Vuong- Lo-Mendell-Rubin test, the Lo-Mendell-Rubin adjusted Likelihood Ratio Test (LRT), and the bootstrapped parametric Likelihood Ratio Test (BLRT). The Vuong-Lo-Mendell-Rubin test and the Lo-Mendell-Rubin adjusted LRT (144.392, p=.63) both suggested that four classes were not sufficient and that five may be needed for a more optimal solution. However, a subsequent examination of the BLRT, which has been suggested to be more reliable when determining class solutions (Nylund et al., 2007; Kline, 2015), suggested that five classes was a more optimal final model solution. Based on these assessments, the five-class solution was ultimately retained for all subsequent analyses. Further, the LCCA model was deemed to have an acceptable fit to the sample safety climate data, addressing Research Question 1. Each class corresponded to a distinct subclimate, determined based on the probabilistic model and patterns of response to the OLSC, answering Research Question 2.

Homogeneity of Climate Perceptions

Although a final class model solution was quantitatively and substantively determined, it was also necessary to statistically determine whether homogeneity of climate perceptions (i.e., agreement) exists in order to substantiate aggregation of individual OLSC perceptions to the subclimate level and to fully address Research Question 2. For multilevel climate research, this justification is typically conducted using traditional grouping variables (e.g., team, department, branch), but subclimate class membership was the appropriate grouping parameter in the context of this research. No matter the grouping variable used, Zohar (2000) advises the following two conditions must be sufficiently met to justify aggregation of safety climate perceptions from individual- to higher-levels: (a) within-group homogeneity showing that group members equally shared perceptions about safety climate, and (b) between-group variance showing that climates differ significantly between one group and another within an organization.

In the case of this study, individual-level OLSC scores were aggregated (i.e., subclimate as the independent variable and the OLSC measure as the dependent variable, was conducted. The results of the ANOVA were significant, $F(1084, 4) = 38.25, p < .000$, indicating significant differences in aggregate OLSC scores between subclimates. As suggested by Zohar and Luria (2005), average within-subclimate agreement was assessed using intraclass correlation (ICC1), reliability of the mean (ICC2), and within-group interrater agreement ($r_{WG(j)}$) statistics (James, 1982; James et al., 1993; Shrout & Fleiss, 1979).

The results represented a significant and large effect size, (ICC[1] = .567), indicating that climate ratings were heavily influenced by subclimate membership (LeBreton & Senter, 2007). Further, significant ICC(2) values suggest that the mean ratings of subclimate members reliably distinguish the five subclimates from one another (see Table 8).

Table 8

Intraclass Correlation Coefficient

	Intraclass Correlation	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	F Test with True Value 0 Value	df1	df2	Sig
Single Measures	.567	.544	.589	20.604	1088	15232	.000
Average Measures	.951	.947	.956	20.604	1088	15232	.000

Note. Two-way random effects model

In the case of the within-group interrater agreement (r_{wg}) statistics, the median $r_{wg(j)}$ = .91 reflects the high degree to which the ratings from different individuals within subclimates were interchangeable (Kozlowski & Hattrup, 1992). Additionally, the mean $r_{wg(j)}$ for each subclimate exceeded the >.70 criterion for consensus as outlined by Glick (1985). In fact, the $r_{wg(j)}$ values ranged from .82 to .93 (Appendix C). When using r_{wg} as a measure of climate strength, a significant, positive correlation was found between climate strength and climate level (r = .259, p = .000). This finding is not surprising given that high climate levels (i.e., higher means) are only obtained when there is strong agreement among group members (Zohar & Luria, 2005).

Taken together, these results suggest acceptable homogeneity of OLSC perceptions existed within the five subclimates. The overall results from the examination of homogeneity of climate perceptions suggest that sufficient between-subclimate variability and within-subclimate agreement were both demonstrated, such that aggregation of OLSC perceptions to the subclimate level was justified, providing further support for the idea that subclimates may be a viable alternative to the suborganizational aggregations (e.g., teams, departments) traditionally used in climate research.

Subclimate Profile Characteristics

Research Question 3

The third research question was about the profile characteristics (e.g., elevation, variability, shape) of each subclimate. To recap briefly, profile elevation is represented by the mean across the three OLSC factors (ME1, LD2, and DI3) for each subclimate, Profile variability is represented by the degree of variability across the factors. That is, variability captures the variance of subclimate member OLSC scores across the three factors and may be viewed as the deviation of OLSC factors from their overall mean. In contrast to profile elevation and variability, profile shape is captured by clustering together individuals with similar patterns of response on OLSC factor scores. This provides a view of the overall pattern of ups and downs across all dimensions, based on the elevation.

It is useful to establish an understanding of the profile characteristics of the organization as well as the profile characteristics of the five distinct subclimates. Doing so helps to establish a context for the subsequent determination of how the five subclimates differ with regard to their respective elevations as well as in relation to the overall organization. Table 9 presents the elevation and variability profile characteristics for the overall organization as well as each subclimate. Table 10 presents the OLSC profile characteristics for the overall organization by factor while Table 11 presents the OLSC profile characteristics for the overall organization and each subclimate by factor.

Table 9

Elevation and Variability Profile Characteristics by Subclimate

Subclimate	Elevation ($\bar{X}$)	Variability (SD)
Organization	3.81	.730
1	3.44	.459
2	3.65	.424
3	3.70	.483
4	3.35	.351
5	3.98	.514

Note. ME1 = Monitoring-Enforcement, LD2 = Learning-Development, DI3 = Declaring-Informing

Table 10

Organization-level Profile Characteristics

	Elevation ($\bar{X}$)	Variability (SD)
ME1	-.005	.027
LD2	.015	.253
DI3	-.065	.361

Note. ME1 = Monitoring-Enforcement, LD2 = Learning-Development, DI3 = Declaring-Informing. Scores on the OLSC factors (i.e., dimensions) were standardized.

Table 11

Subclimate and Organization Profile Characteristics by OLSC Dimension

Factor	Subclimate/Org	Elevation ($\bar{X}$)	Variability (SD)
ME1	1	.567	.040
	2	-.264	.042
	3	.201	.028
	4	.545	.026
	5	-.005	.027
	Organization	.050	.267
LD2	1	.399	.055
	2	-.232	.051
	3	.273	.031
	4	-.285	.034
	5	-.003	.030
	Organization	.015	.253
DI3	1	-.966	.049
	2	.496	.026
	3	-.474	.020
	4	-.260	.052
	5	.008	.022
	Organization	-.065	.361

Note. ME1 = Monitoring-Enforcement, LD2 = Learning-Development, DI3 = Declaring-Informing. Scores on the OLSC factors (i.e., dimensions) were standardized.

Hypothesis 2

Hypothesis 2 was that subclimates would differ based on profile characteristics. To determine whether subclimates differed, the standardized profile elevations for the five subclimates were plotted (Figure 5).

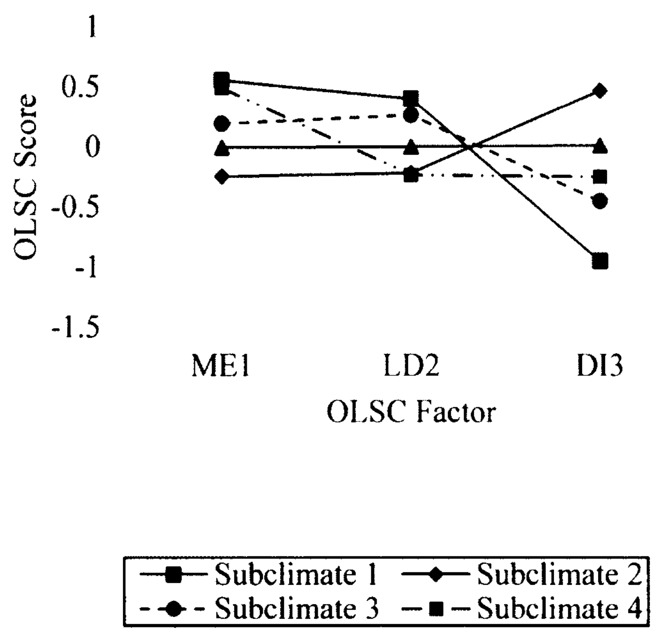

Figure 5. Subclimate Profiles (i.e., Configurations). Scores on the OLSC factors (i.e., dimensions) were standardized to facilitate interpretation of the configurations.

When viewing this information at a more granular level, there appear to be some differences in how subclimate groups rated climate perceptions for the three OLSC factors (ME1 than for LD2 or DI3) relative to each other. Schulte and Ostroff (2014) suggest that contrasts between the shapes of the five subclimate configurations can be determined visually. Using this process, Subclimates 1 and 3 can be said to have a similar shape. That is, these subclimates are both high on ME1 and LD2 and low on DI3 and can be characterized as high-high-low in their response endorsements. Using the same process, Subclimate 2 exhibits a mod-mod-high endorsement pattern, while Subclimate 4 may be described as high on ME1 and low on both LD2 and DI3. Subclimate 5 is moderate across all three safety climate dimensions.

When viewing the subclimate profile shapes relative to the overall organizational configuration (Figure 6), the relative position of each subclimate can be examined.

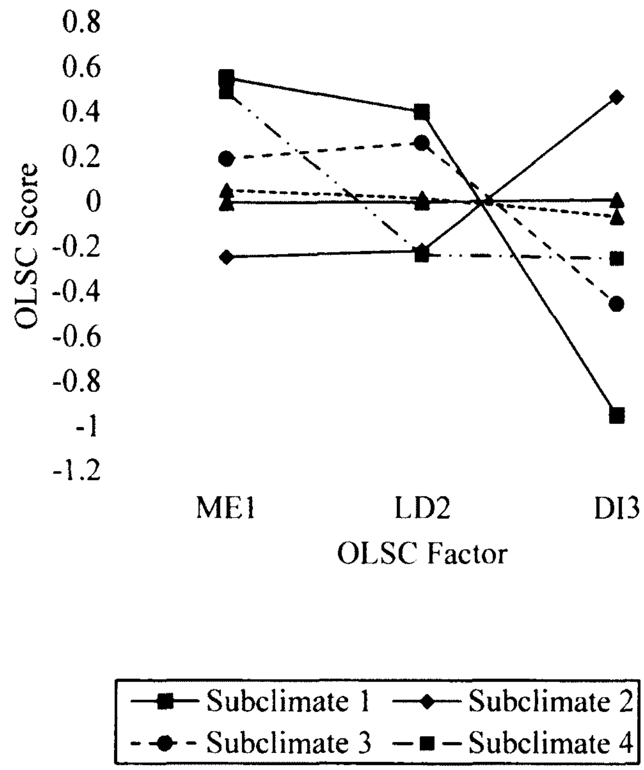

Figure 6. All Configurations. Note. Scores on the OLSC factors (i.e., dimensions) were standardized to facilitate interpretation of the configurations.

A visual inspection of Figures 5 and 6 indicates that there are differences in how groups endorse the OLSC relative to each other and the overall organization. For example, it appears that Subclimate 5 is closely aligned with the organization configuration and that Subclimate 1 and Subclimate 2 endorse DI3 differently. Visual profile examination provides no information, however, on how the subclimates differ in terms of characteristics other than response patterns.

Subclimate Demographic Characteristics

Research Question 4

The fourth, and final, research question concerned whether subclimates were different in terms of demographic attributes. A nonparametric Kruskal-Wallis test was conducted to determine whether demographic attributes varied as a result of subclimate membership. The demographic variables included in the test were job function, education level, age group, and organizational tenure. The results of the test indicated a statistically significant difference existed only for job function X^2 (4) = 14.68, p = .005. Post-hoc Mann-Whitney tests were conducted to evaluate pairwise differences among the five subclimates on job function, controlling for Type I error using the Holm sequential Bonferroni approach (Holm, 1979). The results indicated a significant difference between Subclimate 2 and Subclimate 5 only (U = 39614, p = .004). Subclimate 5 exhibited a greater proportion of upper management employees than Subclimate 2 (Table 11). Thus, in this sample two of the five subclimates did exhibit differences in terms of the demographic attribute of job function, answering Research Question 4.

Table 12

*Job_Fx * Subclimate Crosstabulation*

			Subclimate					
			1	2	3	4	5	Total
Job_Fx	Upper Mgmt	Count	$17_{a,b}$	64_{b}	$112_{a,b}$	$39_{a,b}$	388_{a}	620
		% within Subclimate	40.5%	45.7%	59.6%	63.9%	59.0%	56.9%
	Middle Mgmt	Count	15_{a}	38_{a}	33_{a}	12_{a}	144_{a}	242
		% within Subclimate	35.7%	27.1%	17.6%	19.7%	21.9%	22.2%
	Non-Super	Count	10_{a}	38_{a}	43_{a}	10_{a}	126_{a}	227
		% within Subclimate	23.8%	27.1%	22.9%	16.4%	19.1%	20.8%
Total		Count	42	140	188	61	658	1089
		% within Subclimate	100%	100%	100%	100%	100%	100%

Note. Job_Fx = Job function group, Each subscript letter denotes a subset of Subclimate categories whose column proportions do not differ significantly from each other at the .05 level.

CHAPTER 4

DISCUSSION

Based on recent suggestions of climate researchers to more closely examine the role of variability in organizational climate emergence (Fulmer & Ostroff, 2015), this dissertation offered an exploratory investigation of perceptual variance in safety climate. By using a patterned emergence perspective to reconceptualize the confines of organizational units as subclimates, rather than formally-defined work groups, this study addressed criticisms that heavy reliance on dispersion composition models (Chan, 1998) and work teams has thwarted the investigation of unobserved organizational subgroups that perceive the organizational climate similarly (Dawson et al., 2008; González-Romá & Peiró, 2014; Kuenzi & Schminke, 2009). To examine these issues, this study conceptualized subclimates as having high climate strength and significant between-group discrimination with regard to their climate perceptions. These groups were quantitatively identified using configural measurement techniques (Meyer et al., 1993; Ostroff & Fulmer, 2014). More specifically, LCCA was utilized to reveal patterns of response, using safety climate as an exemplar. Overall, support was found for both hypotheses of this study. That is, the hypothesized factor structure of the OLSC was replicated, and safety subclimates were found to differ based on their respective profile characteristics. This study also shed light on several core research questions related to the examination and typing of safety subclimates. The results of this study, to include potential limitations and directions for future research, are discussed in the subsequent sections.

Relating Core Findings to Key Conceptual Attributes of Safety Climate

In order to use LCCA as a technique to group individuals based on patterns of response, the factor structure of the measurement scale being used had to first be confirmed via CFA. As safety climate was chosen as the exemplar for this study, the OLSC (Zohar & Luria, 2005) was used for this purpose. The hypothesized structure between the observed OLSC items and underlying OLSC factors was tested statistically to determine its fit to the sample data. As reported, the results of the CFA and evaluation of the corresponding measurement model indicated adequate fit of the hypothesized three- factor structure of the OLSC, supporting Hypothesis 1 and replicating the previous findings of Johnson (2007).

Before discussing the core research questions and hypothesis related to LCCA and subclimates, an important point related to the CFA is worthy of further discussion. That is, there are paradoxical sets of goals that should be expressly understood when confirming the factor structure of a measure on sample data prior to using configural measurement techniques to identify subclimates. Standard data screening procedures for CFA require that multivariate skewness and kurtosis be assessed and addressed if abnormal (DeCarlo, 1997). As outlined in the results section, an examination of Mardia's (1970, 1974) multivariate kurtosis coefficient indicated that kurtosis was problematic, and 82 outlier cases were identified and removed from the data set in an attempt to address this issue. However, the study of perceptual variability based on a patterned emergence compilation perspective assumes nonuniform distributions exist within the overall climate of an organization (Fulmer & Ostroff, 2015). This creates a situation whereby researchers must be mindful of meeting the assumptions of multivariate normality whilst understanding the potential side effects of aggressively addressing skewness and kurtosis prior to subclimate identification. That is, a myopic focus on achieving uniform, normally distributed data may remove meaningful variance arising from true subgroup differences within the sample and may ultimately result in inaccurate subclimate identification. As established guidelines do not exist to govern these decisions, the assumptions underpinning LCCA were followed to determine the extent to which the sample data set was modified by removing cases to reduce kurtosis.

Once the issue of multivariate kurtosis had been addressed, the results of this study indicated that LCCA did in fact yield a model that had an acceptable fit to safety climate data. In addition, a five-class model could be identified based on patterns of response along the three OLSC factors identified via the CFA. Perhaps more importantly, each class in the model corresponded to a distinct safety subclimate as jointly determined by the probabilistic model, patterns of response to the OLSC, and tests of homogeneity of climate perceptions. Regarding the tests of homogeneity of climate perceptions, results suggested that safety climate ratings were heavily influenced by subclimate membership and that the five safety subclimates could be reliably distinguished from one another. But how, exactly, do these findings help to inform and add value to the climate literature generally and the safety climate literature in particular? To answer this question, it is necessary to relate the findings regarding subclimate profile characteristics to several key facets of the safety climate construct.

When considering homogeneity and variability of climate perceptions between-subclimates, and how group membership may influence safety climate ratings, a number of key facets help to explain the organizational pressures that may result in the perceptions of subclimate members becoming more or less similar to each other. The first key facet of safety climate is that the organizational environment is complex, and the assessment of organizational priorities may be cognitively challenging for employees. Safety-related policies, practices, and procedures form building blocks of the organizational environment. The relationships between these elements and the relative priorities among them inform individual perceptions of safety climate (Zohar, 2000). Organizations with strong safety systems exhibit consistent application of visible and salient policies, practices, and procedures. Consistency, in turn, creates the conditions under which individuals uniformly interpret the signals sent by the system, thereby leading to the formation of similar safety climate perceptions (Bowen & Ostroff, 2004; Zohar, 2010). However, the overall pattern and signals must be sorted out for individuals to discern what safety-related behaviors are rewarded, expected, and supported. When leaders enable situations where there are competing domains, such as a trade-off of safety-related policies to meet production goals, conflict is created and employees receive a signal regarding the relative importance of safety. If trade-offs are witnessed, a lower priority of safety may be perceived which would be reflected in lower individual safety climate ratings and, relatedly, lower climate levels.

The second key facet safety climate is that the alignment between leaders' espousals (e.g., words) and enactments (e.g., deeds) with regard to safety priorities may inform employee behavior-outcome expectancies. Employee's expectancies, in turn, help to inform their climate perceptions. Similar to the situation where competing domains create conflicting messages, inconsistencies or gaps between espousals and enactments may signal that safety is not an organizational priority and may also result in lower climate levels.

The third key facet that may affect safety climate perceptions is the consistency perceived by employees regarding safety-related policies, procedures, and practices. If these formalized edicts are viewed as incongruent or mutually exclusive, individuals may perceive a lack of consistency and, as a result, form a lower perceived priority for safety. This, also, would result in a lower climate level.

When relating these key conceptual attributes to the findings of this study, it would seem reasonable to simply compare and contrast the climate levels to pinpoint which subclimates may have lower perceived safety climate relative to one another and to the organization as a whole. However, this approach underscores a larger problem in the practice of using climate measures as diagnostic tools in organizations. That is, it is not uncommon for practitioners and researchers alike to rely heavily on the interpretation of an organization's safety climate based solely on climate level as the measurement parameter of interest (Fulmer & Ostroff, 2015; Schneider et al., 2002; Zohar, 2003). However, strict reliance on climate level (i.e., mean climate scores), synonymous with elevation in configural measurement approaches, can mask important variations in scale endorsement and can lead to erroneous conclusions with regard to the how employees perceive the organizational climate (Zohar & Luria, 2005).

Referring back to Table 9, Subclimate 5 had the highest mean climate level rating ($\bar{X}$=3.98) relative to the other subclimates and Subclimate 4 had the lowest ($\bar{X}$=3.35). For reference, the global, or overall, organizational climate level rating was lower than Subclimate 5 but higher than all other subclimates ($\bar{X}$=3.81). Although it is possible that the effects of some of these key conceptual attributes were at play and might have affected Subclimate members' perceived priority for safety, and consequently, their respective climate ratings, the underlying drivers for ratings are not apparent from simply reviewing the climate level data. All that may be determined from a review of the respective climate levels is that some groups perceive a lower or higher organizational priority for safety relative to each other, and the organization as a whole. Ehrhart, Schneider, and Macey (2013) recently advised caution when interpreting global climate levels based on the amount of within-group variance (e.g., climate strength) that is present. That is, if there is high within-subclimate variance, the global climate level would be more unreliable, and would thus not be a meaningful measure of central tendency. In the case of this study, then, when comparing the five subclimate characteristics against the overall, or global, organizational climate characteristics, questions emerge with regard to how meaningful the global organizational safety climate level is as a diagnostic given the differences in variability between Subclimates 4 (SD = .351) and 5 (SD = .514), for example.

Practically speaking, one obvious advantage of using subclimate as a grouping variable is that subclimates help to contextualize within-group agreement and between-group variation by grouping individuals together that respond similarly across climate factors rather than examining climate level or climate strength in isolation. Referring to Table 11 and Figures 5 and 6, an examination of the elevation, variability, and shape of each subclimate shows that there are qualitative inconsistencies with regard to how subclimates respond to the OLSC. When considering the patterns of response along the OLSC factors, Subclimates 1 and 3 were found to have similar shapes. That is, members of both subclimates tended to respond high on ME1 and LD2 and low on DI3 and were qualitatively characterized as exhibiting high-high-low pattern. Using the same process, Subclimate 2 exhibited a moderate-moderate-high pattern, while Subclimate 4 was typed as high-low-low. Subclimate 5 was found to be moderate across all three safety climate dimensions (i.e., moderate-moderate-moderate) and shared a similar elevation and shape with the overall organization.

While the results indicate differences, or inconsistencies, in how groups endorsed the OLSC factors relative to each other and the overall organization, they provide no additional information on how the subclimates differ in terms of other characteristics. As previously discussed in the review of the climate literature, organizational theorists suggest that inconsistencies are normal in organizations. The characterizations of organizations as organized anarchies (Cohen et al., 1972) and loosely coupled systems (Weick, 1979) suggest that the perception of inconsistencies by individuals, operationalized within their personal and social contexts, may result in variation in climate perceptions between groups (Zohar & Tenne-Gazit, 2008). In the case of the present study, the demographic characteristics of each subclimate were examined to see if any significant differences existed. The results indicated a statistically significant difference between Subclimate 2 and Subclimate 5. Subclimate 5 exhibited a greater proportion of upper management employees and Subclimate 2 exhibiting a greater proportion of non-supervisory employees.

Sources of Safety Climate Emergence and Alignment

An additional key facet of safety climate is that it is derived from shared perceptions regarding psychologically meaningful attributes of the organizational environment (Zohar, 2010) and that it is socially-shared through a variety of mechanisms, which ultimately results in the emergence and alignment of climate perceptions. Notably, this conceptualization of safety climate is in line with recent recommendations that researchers obtain construct validity evidence for the alignment of climate perceptions (i.e., climate strength) rooted in processes of climate emergence (Chan, 2014) and helps to explain the importance of considering socially-derived influences on climate formation (Schneider & Reichers, 1983). From a conceptual standpoint, the investigation of subclimate demographic characteristics may help to address a key theoretical question related to the process though which safety climate perceptions converge and why subclimate members with similar positions in the organizational hierarchy, as opposed to members of work teams or departments, would engage in activities that would result in safety climate emergence and perceptual alignment at the subclimate level.

The work of Ostroff and colleagues (2003) and Zohar (2010) identify symbolic social interaction and shared supervisory leadership as the two primary antecedents likely to promote climate emergence and alignment of perceptions. These antecedents may help to explain the statistically significant differences found in this study between Subclimates 2 and 5. Symbolic interactionism is a philosophy that posits that meaning and reality are socially construed (Berger & Luckmann, 1967) and gradually arise from normative exchanges between individuals (Blumer, 1986; Stryker, 1980). The interactive approach to climate formation uses symbolic interactionism as a philosophical basis to help explain how shared perceptions of the work environment ultimately generate from unit member social interactions (Moran & Volkwein, 1992; Schneider & Reichers, 1983). More specifically, symbolic social interaction is a theoretical framework that seeks to explain how the emergence of organizational climate perceptions is thought to be subject to social influence through a sensemaking process (Weick, 1995), whereby individuals attempt to interpret and explain complex cues from their work environment (Ostroff et al., 2003; Schneider & Reichers, 1983; Weick, 1993; Weick et al., 2005).

The interactive approach posits that social interaction fosters communication and discussion necessary to develop a shared interpretation and cognitive appraisal of the work environment (Rentsch, 1990). Rentsch studied members of interaction clusters defined by sociometric methods and found that they tended to attribute similar meanings to organizational events. Conversely, those members involved in different interaction clusters attributed different meanings to the organizational events. Similarly, Klein and colleagues (2001) used the frequency of collaboration as an indicator of social interaction and found significant positive correlations between social interaction and climate strength, lending support to the idea that perceptual alignment occurs as a result of social interaction processes. With regard to safety climate, the role of symbolic interactions and sensemaking as antecedents has not been widely studied. However, Zohar and Tenne-Gazit (2008) used social-network techniques as a proxy for sensemaking processes, and found a positive relationship between the frequency of social exchanges and density of communication networks and the degree of within-unit alignment (i.e., climate strength) among unit members' climate perceptions. Similar to the interactive approach to climate formation (Moran & Volkwein, 1992; Schneider & Reichers, 1983), climate strength is thought to evolve from social interactions.

Another primary antecedent likely to promote the emergence of shared safety climate perceptions is leadership. This is consistent with the wider climate literature, which has long held the proposition that leaders helped to create climate (Lewin et al., 1939). The safety climate literature has largely explained the consistent safety climate-leadership relationship by specifying that group members repeatedly observe their leaders and exchange information with them through a process of social learning, and that this process is meant to interpret the complex organizational environment (Dragoni, 2005; Morgeson & Hofmann, 1999; Zohar, 2003; Zohar & Luria, 2004; Zohar & Tenne-Gazit, 2008). From this perspective, leaders routinely function as a source of information with regard to relative safety priorities as well as the safety-related behavior that is expected and rewarded by the organization.

Within the context of multilevel safety climate, Zohar and Luria (2005) contend that cross-level alignment dictates that between-groups variation is likely the product of the discretion afforded supervisors in the practical execution of organizational policies and procedures related to safety. That is, formal policies and procedures are formulated and defined at the organizational (i.e., upper management) level and then executed at lower, subunit levels by supervisors. As such, variations in practice can result in between-groups variability in safety climate perceptions. Zohar and Luria posit that organizational-level and subunit-level safety climates should, however, be globally aligned since group variation should be limited based on policies setting limits on group-level interpretations.

The work on cross-level alignment and leadership in the safety climate literature has, notably, been conducted on level-adjusted scales with a referent shift for the group level from the organization's top management to the supervisor. In the case of this study, however, referent-shift consensus scales were not used and would not be relevant since subclimates are an unobserved subpopulation, identified and derived via LCCA, and conceptually different from formalized suborganizational aggregates. Yet, it is nevertheless worthwhile to examine the alignment between global safety climate level and subclimate safety climate levels to understand whether Zohar and Luria's arguments regarding between-group variation in safety climate may be extended to include socially-derived, rather than structurally-derived, antecedents to climate formation.

A potential explanation for the finding of significant differences between the two safety subclimates, which may be usefully characterized as "Worker" (Subclimate 2) and "Upper Management" (Subclimate 5), may be rooted in the diversity literature rather than in the work Zohar and Luria (2005, 2010) have done on leadership and cross-level alignment. Turning from the structural processes through which safety climate perceptions emerge to the sources of shared perceptions, questions remain regarding why the members of the Worker and Upper Management subclimates would engage in activities that would result in perceptual alignment. To date, very little research has addressed this question. Zohar (2010) contends that the complexity of the organizational environment, to include the presence of competing values (Quinn & Rohrbaugh, 1983), competing operational demands (Lawrence & Lorsch, 1967), discrepancies between espousals and enactments (Simons, 2002), and cross-level variations in policy implementation (Zohar & Luria, 2005), all play a significant role and that the ambiguity of the organizational environment drives employees to engage in social- and interpersonal-based processes and activities to interpret signals and derive patterns from the complexity. Given that there is a long history of research showing that group characteristics create a distinctive social context to which individuals respond (Cannella, Park, & Lee, 2008; Pelled, Eisenhardt, & Xin, 1999), it is curious that perceptual alignment of safety climate has been infrequently examined in connection with demographics. On the one hand, climate researchers have acknowledged that the socially-derived characteristics of groups may influence sensemaking processes (Weick, 1995) and, subsequently, the convergence or divergence of climate perceptions (Colquitt et al., 2002; Schneider, Salvaggio, & Subirats, 2002). On the other hand, few researchers have considered how systematic perceptual differences may be linked to demographic characteristics (see Beus et al., 2010; Zohar & Tenne-Gazit, 2008 for exceptions related to safety climate).

Some insight into why Workers and Upper Management may differ significantly with regard to climate perceptions may be derived from previous research on collective climates. As previously stated, González-Romá and colleagues (1999) examined whether membership in collective climates, which are conceptually similar to subclimates, was related to membership based on department, hierarchical level, shift, job location, and organizational tenure. They found that only hierarchical climates (i.e., top managers versus middle-to low-level employees) were significantly related to group membership, and suggested that collective climates gain psychosocial meaning based on the penetration of the top managers' views through other hierarchical levels. The authors posited that the relationship between collective climate and hierarchical level revealed the scope of the top managers' views by revealing two distinct views of the organization — one held by top managers and the other by lower-level employees. Their findings suggested that hierarchical level may be a factor in the formation of organizational climates, which may help to explain the significant finding between job function and Subclimates 2 and 5.

Although the safety climate literature has tended to focus on the role of leader-member exchange and the quality of those relationships as an antecedent to climate emergence, researchers have also acknowledged that because group members are apt to interact more often with each other than with individuals in other groups, they are more likely to develop shared interpretations and meanings for the organizational environment and, consequently, perceptions of both the group safety climate as well as the global organizational safety climate (Huang et al., 2013). However, safety climate studies investigating the role of social interaction in climate formation continue to focus on intact work teams, departments, and branches, given the role and proximity of supervisory discretion in implementing safety practices at tactical (i.e., proximal) levels. The diversity literature may better explain the motivation for shared safety climate perceptions within subclimates by more fully explicating the principles and social processes by which members strive for shared perceptions. For example, the principles of homophily help to explain how demographics may be related to social interaction and climate emergence. Homophily can be defined as the concentration of network connections and social relationships among individuals who are similar with regard to demographic characteristics (McPherson et al., 2001). With regard to social networks in organizations, Festinger's (1954) theory of social comparison guides the classic argument that individuals utilize as a referent group those who are similar to them. According to the principles of homophily, individuals who share demographic characteristics are more likely to share similar histories, narratives, experiences, and attitudes, which facilitates interaction and smooths communication. Research on homophily has shown that increased diversity affects the tendency for social relationships to exhibit homophily and that social networks in diverse environments tend to be more homogenous with regard to demographic, behavioral, and interpersonal characteristics (McPherson et al., 2001). With regard to the formation of shared climate perceptions, homophily is important to consider because it affects individuals' social systems and consequently, may constrain the information they receive and interactions they experience in the organizational environment. Findings in research on homophily have been largely consistent with findings in diversity research in that demographic dissimilarity has been shown to affect team processes and outcomes (Milliken & Martins, 1996; van Knippenberg, De Dreu, & Homan, 2004) and that diversity impairs group cohesion and communication (Williams & O'Reilly, 1998). Hence, the principles of homophily and diversity may help to explain how perceptual convergence could be related to an attribute like job function within subclimates.

In a similar vein, the similarity-attraction paradigm (Byrne, 1971) explains that people form in- and out-groups on the basis of perceived similarity, and that these groups are codified for individuals through the process of social categorization and social identity. Diversity research has shown that people use demographic attributes as a means for determining similarity, identification, and classification into subgroups (Harrison, Price, Gavin, & Florey, 2002; Horwitz & Horwitz, 2007; Tsui, Egan, & O'Reilly III, 1992). Optimal distinctiveness theory (Brewer, 1991; Brewer, Manzi, & Shaw, 1993; Hornsey & Hogg, 1999; Pickett & Brewer, 2001) helps to explain that individuals seek an optimal balance of uniqueness and identity. That is, individuals desire to belong to a particular group that holds meaning for them, such as line of business or occupation, but also desire to be distinctive from other groups. Similarly, social and psychological distance theories (Hraba, Hagendoorn, & Hagendoorn, 1989; Jetten, Spears, & Postmes, 2004) have been drawn upon to explain the desire for subgroups to be distant from one another (Bezrukova, Jehn, Zanutto, & Thatcher, 2009) and social distance theories, in particular, help explain how in- and out-group formation entails an assessment of the extent to which out-groups are different from in-groups. Constructed social representations, such as nationality, ethnicity, occupation, or other demographic attributes can also result in perceived distances between groups (Hraba et al., 1989).

Overall, there is no definitive indication of why Workers and Upper Management differed in their safety climate response patterns. However, these social- and diversity-related theories may help to explain the structure of subclimate demographic composition and why it may matter for subclimate processes and functioning. These theories are also helpful in explaining how subclimates may vary in terms of their social interaction patterns or social and normative expectations (Morgeson & Hofmann, 1999) and, moreover, how the effects of these social processes could promote the alignment of climate perceptions among members of the same subclimate, and divergence between members of different subclimates.

Limitations and Future Research

Before highlighting the practical and theoretical contributions of this study, it is imperative to first acknowledge several limitations and potential directions for future research. First, the exploratory nature of the research meant that no causal relationships were modeled or examined between subclimate membership and objective safety outcomes. As such, the predictive and criterion-related validity of the OLSC was not established. Previous research on safety climate has shown that the inclusion of relevant outcome variables, such as safety performance metrics, audits, and behavioral observations, may support the predictive and criterion-related validity of perceptual data (Zohar & Luria, 2004; Zohar & Tenne-Gazit, 2008). While the CFA did lend psychometric evidence for the validity of a three-factor structure for the OLSC, the scale is a self-report measure. As such, it is possible this study may have suffered from common method bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Previous safety climate studies (Zohar & Luria, 2004; Zohar, 2003) have employed techniques such as random split procedures to reduce single source bias, which should be considered in any future research.

Second, this study was cross-sectional and data were only gathered at one point in time. Thus, investigation of fluctuations in subclimate membership was not possible. In order to further examine the causal ordering of variables among subclimate membership, social interaction, and perceptual alignment, for example, it would be helpful to employ a longitudinal design which allows for the measurement of social interaction and climate consensus at multiple points in time.

Third, with regard to the sample, the data were gathered from a single organization. Caution should therefore be used in generalizing the results of this study to other populations. In addition, the sample of respondents was predominantly male. In the limited research that has been conducted on the relationships between demographics and safety climate, there is some evidence to support the idea that men tend to experience accidents more frequently than women. For example, Byrnes, Miller, and Schafer (1999) found that men are higher than women in risk taking and sensation seeking. They also found significant shifts in the gender gap related to age, and that the gap grew smaller over time. Given the high proportion of males in the sample data, future research should consider whether gender has any association to safety subclimate membership.

Several methodological limitations should be addressed in future investigations. While the within-group interrater agreement statistics reflected the high degree to which the ratings from different individuals within subclimates were interchangeable and that each distinct subclimate exhibited acceptable levels of consensus, testing of alternative distributions was not done. That is, this research utilized the accepted approach of using the uniform (i.e., rectangular) null distribution when estimating within-subclimate agreement (LeBreton, Burgess, Kaiser, Atchley, & James, 2003). However, there have been discussions pointing out the theoretical and practical problems associated with its use. For example, the uniform distribution assumes no response bias and that each response option is equally likely to be selected on a Likert scale (Bliese, 2000; LeBreton & Senter, 2007; Likert, 1967). Thus, the uniform distribution does not account for expected random variance (Brown & Hauenstein, 2005). However, climate research has shown that responses may not conform to a uniform distribution due the effects of response biases (James et al., 1984). In the case of safety climate, Zohar and Tenne-Gazit (2008) have noted that the rectangular distribution also does not take into account the prevalence of restricted ranges in responses to safety climate surveys. Finally, Schneider and colleagues (2002) have noted that there is a likelihood of r_{wg} resulting in values greater than one, which may be difficult to interpret and overestimate the degree of within-group agreement. For all of these reasons, it is possible that the use of an alternative distribution (e.g., triangular, skewed) may have more accurately estimated the variance expected under conditions of random response in this sample (James et al., 1984).

Another potential methodological limitation is that the use of LCCA allows for subjectivity in model estimation. As such, there is a chance of employing a less than optimal estimation method and incorrectly specifying the measurement model. It is worth noting that modification indices calculated as a part of the CFA provided some indication that moving one of the items to a different factor may have potentially improved model fit. However, given the controversies and risks associated with the practice of relying on modification indices for model re-specification (Jackson et al., 2009), and given the evidence that the model tested exhibited acceptable fit, the model was not respecified. The subjectivity afforded researchers in making these kinds of analytical decisions should be weighed carefully in future research.

This study points to some exciting avenues for future research with subclimates. For example, although the ICC(1) values indicated that climate ratings were heavily influenced by subclimate membership (LeBreton & Senter, 2007) and the significant ICC(2) values suggested that the mean ratings of subclimate members reliably distinguish the five subclimates from one another, item-level response patterns were not examined. In-depth analysis of which specific items show agreement within subclimates could help to design and target intervention plans to help strengthen or increase alignment of climate (Bliese, 2000). Additionally, profiling patterns of response patterns may yield tailored practical interventions targeted at strengthening climate in specific groups (Zohar & Hofmann, 2012). The in-depth examination of item-level response patterns may help to elucidate the degree to which these groups are aligned (Ostroff & Fulmer, 2014) with regard to the overall organizational climate, and may provide a rich diagnostic tool to differentiate groups when taking a multilevel perspective of climate.

Contributions and Concluding Thoughts

In their extensive review on the state of organizational climate research, Kuenzi and Schminke (2009) note that the historical focus on the predefined work group is reflective of a tendency of researchers to fixate on the quantitative demonstration of within-group consensus to justify aggregation of perceptions from the individual to higher levels, rather than on the conceptual understanding of how and why patterns of similar perceptions may emerge outside these confines. This dissertation attempted to address the issue by examining perceptual variability via a patterned emergence compilation model (Fulmer & Ostroff, 2015), whereby nonuniform patterns of dispersion (i.e., distributions) were identified using configural measurement techniques (Wang & Hanges, 2011). These patterns corresponded to groups that were conceptualized as subclimates. Subclimates were characterized by high within-group agreement (i.e., climate strength) and significant between-group discrimination in climate perceptions. By investigating subclimates, this research answered the call to examine climate as a differentiated phenomenon (Schneider & Barbera, 2014), rather than from a traditional, integrationist perspective (Martin, 2001).

Overall, this research established the viability of LCCA as a measurement tool for identifying subclimates, and for using subclimates as a grouping variable for the investigation of safety climate variability. It is also worth noting that this research contributed to both the general climate and general multilevel modeling literatures by showing that subclimates may be formed by climate response patterns and that these patterns may be differentiated according to the demographic of job function. This research also contributed to moving the safety climate literature away from reliance upon the work group as a grouping variable and dispersion models as the default basis to explain the nature and operation of perceptual variability. Finally, the finding of significant differences in safety climate perceptions between Subclimates 2 and 5 provides a novel argument for the role of job function as a potential source of safety climate emergence and alignment.

Given the increasing diversity of the organizational ecosystem, it is hoped that the findings of this study encourage other organizational scholars to examine the degree to which unidentified subgroups converge or diverge with regard to climate perceptions. Furthermore, it is hoped that this study offers a means by which to articulate how competing pressures for homogeneity and variability may be separated from the dominant view that shared supervisory influence is the primary antecedent to climate emergence and strength. Finally, it is hoped that by using the diversity literature to engage in a closer examination of how the subclimates may differ in terms of socially-derived characteristics, this study answered the longstanding call to continue the exploration of the etiology of climates from new and unique perspectives (Schneider & Reichers, 1983).

REFERENCES

Aldenderfer, M. S., & Blashfield, R. K. (1978). Cluster Analysis and Archaeological Classification, 502.

Argyris, C. (1957). The individual and organization: Some problems of mutual adjustment. *Administrative Science Quarterly*, 1-24.

Argyris, C. (1958). Some problems in conceptualizing organizational climate: A case study of a bank. *Administrative Science Quarterly*, 501-520.

Bacher, J. (2000). A probabilistic clustering model for variables of mixed type. *Quality and Quantity, 34*(3), 223-235.

Barnard, C. I. (1938). *The functions of the executive*. Cambridge, MA: Harvard University Press.

Barrett, P. (2007). Structural equation modeling: Adjudging model fit. *Personality and Individual Differences*, *42*, 815– 824.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238 –246.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*, 588-606.

Berger, P. L., & Luckmann, T. (1967). *The Social Construction of Reality: A Treatise in the Sociology of Knowledge*: Anchor books.

Bergman, M. E. (2011). Agreement, Disagreement, and a Person-Centered Psychology of Working. *Industrial and Organizational Psychology, 4*(1), 131-135.

Beus, J. M., Payne, S. C., Bergman, M. E., & Arthur, W., Jr. (2010). Safety climate and injuries: An examination of theoretical and empirical relationships. *Journal of Applied Psychology, 95*(4), 713.

Bezrukova, K., Jehn, K. A., Zanutto, E. L., & Thatcher, S. M. (2009). Do workgroup faultlines help or hurt? A moderated model of faultlines, team identification, and group performance. *Organization Science, 20*(1), 35-50.

Blau, P. M., & Scott, W. R. (1962). *Formal organizations: A comparative approach.* Stanford University Press.

Bliese, P. D. (2000). Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In K. J. Klein & S. W. Kozlowski (Eds.), Multilevel Theory, Research, and Methods in Organizations (pp. 349-381). San Francisco, CA: Jossey-Bass.

Bliese, P. D., & Halverson, R. R. (1998). Group size and measures of group-level properties: An examination of eta-squared and ICC values. *Journal of Management, 24*(2), 157-172.

Blumer, H. (1986). *Symbolic interactionism: Perspective and method.* Englewood Cliffs, NJ: Prentice-Hall.

Boomsma, A. (2000). Reporting analyses of covariance structures. *Structural Equation Modeling, 7*(3), 461-483.

Bowen, D. E., & Ostroff, C. (2004). Understanding HRM–firm performance linkages: The role of the "strength" of the HRM system. *Academy of Management Review, 29*(2), 203-221.

Box, G. E. (1949). A general distribution theory for a class of likelihood criteria. *Biometrika, 36*(3/4), 317-346.

Box, G. E. (1954). Some theorems on quadratic forms applied in the study of analysis of variance problems, I. Effect of inequality of variance in the one-way classification. *The Annals of Mathematical Statistics, 25*(2), 290-302.

Brewer, M. B. (1991). The social self: On being the same and different at the same time. *Personality and Social Psychology Bulletin, 17*(5), 475-482.

Brewer, M. B., Manzi, J. M., & Shaw, J. S. (1993). In-group identification as a function of depersonalization, distinctiveness, and status. *Psychological Science, 4*(2), 88-92.

Brown, K., & Kozlowski, S. (1999). *Dispersion theory: Moving beyond a dichotomous conceptualization of emergent organizational phenomena.* Paper presented at the 14th annual meeting of the Society of Industrial and Organizational Psychology, Atlanta, GA.

Brown, R. D., & Hauenstein, N. M. (2005). Interrater agreement reconsidered: An alternative to the rwg indices. *Organizational Research Methods, 8*(2), 165-184.

Brown, R. L., & Holmes, H. (1986). The use of a factor-analytic procedure for assessing the validity of an employee safety climate model. *Accident Analysis and Prevention, 18*(6), 455-470.

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York, NY: Guilford.

Browne, M. W. (1984), Asymptotically distribution-free methods for the analysis of covariance structures. *British Journal of Mathematical and Statistical Psychology, 37*, 62–83. doi:10.1111/j.2044-8317.1984.tb00789.x

Burdenski, T. K., Jr. (2000). Evaluating Univariate, Bivariate, and Multivariate Normality Using Graphical Procedures. *Multiple Linear Regression Viewpoints, 26*(2), 15-28.

Burke, M. J., Finkelstein, L. M., & Dusig, M. S. (1999). On average deviation indices for estimating interrater agreement. *Organizational Research Methods, 2*(1), 49-68.

Burke, W. W. (2011). A Perspective on the Field of Organization Development and Change The Zeigarnik Effect. *The Journal of Applied Behavioral Science, 47*(2), 143-167.

Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. Routledge.

Byrne, D. E. (1971). *The attraction paradigm* (Vol. 11). New York: Academic Press.

Byrnes, J. P., Miller, D. C., & Schafer, W. D. (1999). Gender differences in risk taking: A meta-analysis. *Psychological Bulletin, 125*(3), 367.

Campbell, J. J., Dunnette, M. D., Lawler, E. E., & Weick, K. E. (1970). *Managerial behavior, performance, and effectiveness*. New York, NY: McGraw-Hill.

Cannella, A. A., Park, J. H., & Lee, H. U. (2008). Top management team functional background diversity and firm performance: Examining the roles of team member colocation and environmental uncertainty. *Academy of Management Journal, 51*(4), 768-784.

Chan, D. (1998). Functional relations among constructs in the same content domain at different levels of analysis: A typology of composition models. *Journal of Applied Psychology, 83*(2), 234.

Chan, D. (2014). Multilevel and Aggregation Issues in Climate and Culture Research. In B. Schneider and K. M. Barbera (Eds.), *The Oxford handbook of organizational climate and culture*, New York, Oxford University Press, p. 484.

Chou, C. P., Bentler, P. M., & Satorra, A. (1991). Scaled test statistics and robust standard errors for non-normal data in covariance structure analysis: A Monte Carlo study. *British Journal of Mathematical and Statistical Psychology, 44*(2), 347-357.

Christian, M. S., Bradley, J. C., Wallace, J. C., & Burke, M. J. (2009). Workplace safety: A meta-analysis of the roles of person and situation factors. *Journal of Applied Psychology, 94*(5), 1103-1127.

Clarke, S. (2006). The Relationship between safety climate and safety performance: A meta-analytic review. *Journal of Occupational Health Psychology, 11*(4), 315-327. doi:10.1037/1076-8998.11.4.315

Clarke, S. (2010). An integrative model of safety climate: Linking psychological climate and work attitudes to individual safety outcomes using meta-analysis. *Journal of Occupational & Organizational Psychology, 83*(3), 553-578. doi:10.1348/096317909X452122

Clarke, S. (2013). Safety leadership: A meta-analytic review of transformational and transactional leadership styles as antecedents of safety behaviours. *Journal of Occupational & Organizational Psychology, 86*(1), 22-49. doi:10.1111/j.2044-8325.2012.02064.x

Clogg, C. C. (1995). Latent class models. *Handbook of statistical modeling for the social and behavioral sciences* (pp. 311-359): Springer.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2013). *Applied multiple regression/correlation analysis for the behavioral sciences*. London, UK: Routledge.

Cohen, M. D., March, J. G., & Olsen, J. P. (1972). A garbage can model of organizational choice. *Administrative Science Quarterly*, 1-25.

Colquitt, J. A., Noe, R. A., & Jackson, C. L. (2002). Justice in teams: Antecedents and consequences of procedural justice climate. *Personnel Psychology, 55*(1), 83-109.

Coyle, I. R., Sleeman, S. D., & Adams, N. (1995). Safety climate. *Journal of Safety Research, 26*(4), 247-254.

Cronbach, L. J., & Gleser, G. C. (1953). Assessing similarity between profiles. *Psychological Bulletin, 50*(6), 456.

Crowley, S. L., & Fan, X. (1997). Structural equation modeling: Basic concepts and applications in personality assessment research. *Journal of Personality Assessment*, *68*(3), 508-531.

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods*, *1*, 16–29.

Dansereau, F., Alutto, J. A., & Yammarino, F. J. (1984). *Theory testing in organizational behavior: The variant approach*. Englewood Cliffs, NJ: Prentice Hall.

Dawson, J. F., González-Romá, V., Davis, A., & West, M. A. (2008). Organizational climate and climate strength in UK hospitals. *European Journal of Work and Organizational Psychology*, *17*(1), 89-111.

DeCarlo, L. T. (1997). On the meaning and use of kurtosis. *Psychological Methods*, *2*(3), 292-307.

Dedobbeleer, N., & Béland, F. (1991). A safety climate measure for construction sites. *Journal of Safety Research*, *22*(2), 97-103.

Dickson, M. W., Resick, C. J., & Hanges, P. J. (2006). When organizational climate is unambiguous, it is also strong. *Journal of Applied Psychology*, *91*(2), 351. doi:10.1037//0021-9010.85.4.587

Doty, D. H., Glick, W. H., & Huber, G. P. (1993). Fit, equifinality, and organizational effectiveness: A test of two configurational theories. *Academy of Management journal, 36*(6), 1196-1250.

Dragoni, L. (2005). Understanding the emergence of state goal orientation in organizational work groups: The role of leadership and multilevel climate perceptions. *Journal of Applied Psychology, 90*(6), 1084.

Dumenci, L. (2011). The Psychometric Latent Agreement Model (PLAM) for discrete latent variables measured by multiple items. *Organizational Research Methods, 14*(1), 91-115.

Ehrhart, M. G. (2004). Leadership and procedural justice climate as antecedents of unit-level organizational citizenship behavior. *Personnel Psychology, 57*(1), 61-94.

Ehrhart, M. G., Schneider, B., & Macey, W. H. (2013). *Organizational climate and culture: An introduction to theory, research, and practice*. New York, NY: Routledge.

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling, 8*, 430 – 457.

Evan, W. M. (1968). A systems model of organizational climate. *Organizational climate: Explorations of a concept*, 107-124.

Everitt, B. S., Stahl, D., Leese, M., & Landau, S. (2011). *Cluster analysis*. London, UK: Wiley.

Fan, X., Thompson, B., & Wang, L. (1999). Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 56-83.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations, 7*(2), 117-140.

Finch, W. H., & Bronk, K. C. (2011). Conducting Confirmatory Latent Class Analysis Using Mplus. *Structural Equation Modeling, 18*(1), 132-151.

Finney, S. J., & DiStefano, C. (2006). Non-normal and categorical data in structural equation modeling. *Structural equation modeling: A second course*, 269-314.

Fleishman, E. A. (1953). The description of supervisory behavior. *Journal of Applied Psychology, 37*(1), 1.

Flin, R., Mearns, K., O'Connor, P., & Bryden, R. (2000). Measuring safety climate: Identifying the common features. *Safety Science, 34*(1), 177-192.

Fulmer, C. A., & Ostroff, C. (2015). Convergence and emergence in organizations: An integrative framework and review. *Journal of Organizational Behavior, 37*(1), 122-145.

George, J. M., & James, L. R. (1993). Personality, affect, and behavior in groups revisited: Comment on aggregation, levels of analysis, and a recent application of within and between analysis.

Gibson, W. A. (1959). Three multivariate models: Factor analysis, latent structure analysis, and latent profile analysis. *Psychometrika, 24*(3), 229-252.

Glendon, A. I., & Litherland, D. K. (2001). Safety climate factors, group differences and safety behaviour in road construction. *Safety Science, 39*(3), 157-188.

Glick, W. H. (1985). Conceptualizing and measuring organizational and psychological climate: Pitfalls in multilevel research. *Academy of Management Review, 10*(3), 601-616.

Glisson, C., & James, L. R. (2002). The cross-level effects of culture and climate in human service teams. *Journal of Organizational Behavior, 23*(6), 767-794.

González-Romá, V., & Peiró, J. M. (2014). Climate and culture strength. In B., Schneider, K. Barbera, (Eds.), *The Oxford handbook of organizational climate and culture*, 496-531.

González-Romá, V., Fortes-Ferreira, L., & Peiró, J. M. (2009). Team climate, climate strength and team performance. A longitudinal study. *Journal of Occupational and Organizational Psychology, 82*(3), 511-536.

González-Romá, V., Peiró, J. M., & Tordera, N. (2002). An examination of the antecedents and moderator influences of climate strength. *Journal of Applied Psychology, 87*(3), 465.

González-Romá, V., Peiró, J. M., Lloret, S., & Zornoza, A. (1999). The validity of collective climates. *Journal of Occupational and Organizational Psychology, 72*(1), 25-40.

Griffin, M. A., & Neal, A. (2000). Perceptions of safety at work: A framework for linking safety climate to safety performance, knowledge, and motivation. *Journal of Occupational Health Psychology, 5*(3), 347-358.

Guion, R. M. (1973). A note on organizational climate. *Organizational Behavior and Human Performance, 9*(1), 120-125, 1103.

Guldenmund, F. W. (2000). The nature of safety culture: A review of theory and research. *Safety Science, 34*(1-3), 215-257.

Harrison, D. A., Price, K. H., Gavin, J. H., & Florey, A. T. (2002). Time, teams, and task performance: Changing effects of surface-and deep-level diversity on group functioning. *Academy of Management Journal, 45*(5), 1029-1045.

Hazy, J. K., & Ashley, A. S. (2011). Unfolding the future: Bifurcation in organizing form and emergence in social systems. *Emergence: Complexity & Organization, 13*(3), 57-79.

Hellriegel, D., & Slocum, J. W. (1974). Organizational climate: Measures, research and contingencies. *Academy of Management Journal, 17*(2), 255-280.

Hofmann, D. A., & Stetzer, A. (1996). A cross-level investigation of factors influencing unsafe behaviors and accidents. *Personnel Psychology, 49*(2), 307-339.

Hofmann, D. A., & Stetzer, A. (1998). The role of safety climate and communication in accident interpretation: Implications for learning from negative events. *Academy of Management Journal, 41*(6), 644-657. doi:10.2307/256962

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 65-70.

Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods, 6*(1), 53-60.

Hornsey, M. J., & Hogg, M. A. (1999). Subgroup differentiation as a response to an overly-inclusive group: A test of optimal distinctiveness theory. *European Journal of Social Psychology, 29*(4), 543-550.

Horwitz, S. K., & Horwitz, I. B. (2007). The effects of team diversity on team outcomes: A meta-analytic review of team demography. *Journal of Management, 33*(6), 987-1015.

House, R., Rousseau, D., & Thomas-Hunt, M. (1995). The third paradigm: Meso organizational research comes to age. *Research in Organizational Behavior, 17*, 71-114.

Hoyle, R. H., & Panter, A. T. (1995). Writing about structural equation models. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 158–176). Thousand Oaks, CA: Sage.

Hraba, J., Hagendoorn, L., & Hagendoorn, R. (1989). The ethnic hierarchy in the Netherlands: Social distance and social representation. *British Journal of Social Psychology, 28*(1), 57-69.

Hu, L. T., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 3*, 424 – 453.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*, 1–55.

Hu, L. T., Bentler, P. M., & Kano, Y. (1992). Can test statistics in covariance structure analysis be trusted? *Psychological Bulletin, 112*, 351–362.

Huang, Y. H., Zohar, D., Robertson, M. M., Garabet, A., Lee, J., & Murphy, L. A. (2013). Development and validation of safety climate scales for lone workers using truck drivers as exemplar. *Transportation Research Part F: Traffic Psychology and Behaviour, 17*, 5-19.

Huberty, C. J., & Petoskey, M. D. (2000). Multivariate analysis of variance and covariance. *Handbook of applied multivariate statistics and mathematical modeling*, (pp. 183-208). New York: Academic Press.

Jackson, D. L., Gillaspy, J. A., Jr., & Purc-Stephenson, R. (2009). Reporting practices in confirmatory factor analysis: An overview and some recommendations. *Psychological Methods, 14*(1), 6.

James, L. R. (1982). Aggregation bias in estimates of perceptual agreement. *Journal of Applied Psychology, 67*(2), 219.

James, L. R., Choi, C. C., Ko, C. H. E., McNeil, P. K., Minton, M. K., Wright, M. A., & Kim, K. I. (2008). Organizational and psychological climate: A review of theory and research. *European Journal of Work and Organizational Psychology, 17*(1), 5-32.

James, L. R., Demaree, R. G., & Wolf, G. (1984). Estimating within-group interrater reliability with and without response bias. *Journal of Applied Psychology, 69*(1), 85.

James, L. R., Demaree, R. G., & Wolf, G. (1993). An assessment of within-group interrater agreement. *Journal of Applied Psychology, 78*(2), 306-309.

James, L. R., James, L. A., & Ashe, D. K. (1990). The meaning of organizations: The role of cognition and values. In B. Schneider (Ed.), *Organizational climate and culture*, (pp. 40-84). San Francisco, CA: Jossey-Bass.

James, L. R., & Jones, A. P. (1974). Organizational climate: A review of theory and research. *Psychological Bulletin, 81*(12), 1096.

Jermier, J. M., Slocum, J. W., Jr., Fry, L. W., & Gaines, J. (1991). Organizational subcultures in a soft bureaucracy: Resistance behind the myth and facade of an official culture. *Organization Science, 2*(2), 170-194.

Jetten, J., Spears, R., & Postmes, T. (2004). Intergroup distinctiveness and differentiation: A meta-analytic integration. *Journal of Personality and Social Psychology*, *86*(6), 862.

Johannesson, R. E. (1973). Some problems in the measurement of organizational climate. *Organizational Behavior and Human Performance, 10*(1), 118-144.

Johns, G. (2006). The essential impact of context on organizational behavior. *Academy of Management Review, 31*(2), 386-408.

Johnson, S. E. (2007). The predictive validity of safety climate. *Journal of Safety Research, 38*(5), 511-521.

Jones, A. P., & James, L. R. (1979). Psychological climate: Dimensions and relationships of individual and aggregated work environment perceptions. *Organizational Behavior and Human Performance, 23*(2), 201-250.

Joyce, W. F., & Slocum, J. W. (1984). Collective climate: Agreement as a basis for defining aggregate climates in organizations. *Academy of Management Journal*, *27*(4), 721-742.

Kaplan, D. (2000). Structural equation modeling: Foundations and extensions. Thousand Oaks, CA: Sage.

Katz, D., & Kahn, R. L. (1966). *The psychology of organizations*. New York, NY: HR Folks International.

Katz, D., & Kahn, R. L. (1978). Organizations and the system concept. *Classics of organization theory*, 161-172.

Kaufman, L., & Rousseeuw, P. J. (2009). *Finding groups in data*. John Wiley & Sons, Inc., New York.

Ketchen, D. J., Thomas, J. B., & Snow, C. C. (1993). Organizational configurations and performance: A comparison of theoretical approaches. *Academy of Management Journal, 36*(6), 1278-1313.

Klein, K. J., Conn, A. B., Smith, D. B., & Sorra, J. S. (2001). Is everyone in agreement? An exploration of within-group agreement in employee perceptions of the work environment. *Journal of Applied Psychology, 86*(1), 3.

Klein, K. J., Dansereau, F., & Hall, R. J. (1994). Levels issues in theory development, data collection, and analysis. *Academy of Management review, 19*(2), 195-229.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford.

Kozlowski, S. W., & Hattrup, K. (1992). A disagreement about within-group agreement: Disentangling issues of consistency versus consensus. *Journal of Applied Psychology*, *77*(2), 161.

Kozlowski, S. W., & Klein, K. J. (2000). A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes.

Kuenzi, M., & Schminke, M. (2009). Assembling fragments into a lens: A review, critique, and proposed research agenda for the organizational work climate literature. *Journal of Management*.

Lance, C. E., Butts, M. M., & Michels, L. C. (2006). The sources of four commonly reported cutoff criteria what did they really say? *Organizational Research Methods, 9*(2), 202-220.

Laudy, O., Boom, J., & Hoijtink, H. (2005). Bayesian computational methods for inequality constrained latent class analysis. *New developments in categorical data analysis for the social and behavioral sciences*, 63-82.

Lawrence, P. R., & Lorsch, J. W. (1967). Differentiation and integration in complex organizations. *Administrative Science Quarterly*, 1-47.

Lazarsfeld, P. F., Henry, N. W., & Anderson, T. W. (1968). *Latent structure analysis*: Houghton Mifflin Boston.

Leavitt, H. J. (1959). *Managerial Psychology: An Introduction to Individuals, Pairs, and Groups in Organizations*: University of Chicago Press.

LeBreton, J. M., & Senter, J. L. (2007). Answers to 20 questions about interrater reliability and interrater agreement. *Organizational Research Methods*.

LeBreton, J. M., Burgess, J. R., Kaiser, R. B., Atchley, E. K., & James, L. R. (2003). The restriction of variance hypothesis and interrater reliability and agreement: Are ratings from multiple sources really dissimilar? *Organizational Research Methods*, *6*(1), 80-128.

Lewin, K. (1936). Some social-psychological differences between the United States and Germany. *Character & Personality*, *4*(4), 265-293

Lewin, K., Lippitt, R., & White, R. K. (1939). Patterns of aggressive behavior in experimentally created "social climates". *The Journal of Social Psychology, 10*(2), 269-299.

Likert, R. (1961). New patterns of management.

Likert, R. (1967). The method of constructing and attitude scale. *Methods and Techniques in Business Research*, 54.

Lindell, M. K., & Brandt, C. J. (2000). Climate quality and climate consensus as mediators of the relationship between organizational antecedents and outcomes. *Journal of Applied Psychology, 85*(3), 331.

Litwin, G. H., & Stringer, R. A., Jr. (1968). Motivation and organizational climate.

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika, 88*(3), 767-778.

Lok, P., Rhodes, J., & Westwood, B. (2011). The mediating role of organizational subcultures in health care organizations. *Journal of Health Organization and Management, 25*(5), 506-525.

Mardia, K. V. (1970). Measures of multivariate skewness and kurtosis with applications. *Biometrika, 57*(3), 519-530.

Mardia, K. V. (1974). Applications of some measures of multivariate skewness and kurtosis in testing normality and robustness studies. *Sankhyā: The Indian Journal of Statistics, Series B*, 115-128.

Marsh, H. W., Hau, K. T., Balla, J. R., & Grayson, D. (1998). Is more ever too much? The number of indicators per factor in confirmatory factor analysis. *Multivariate Behavioral Research, 33*, 181–220.

Martin, J. (1992). *Cultures in organizations: Three perspectives*. New York, NY, Oxford University Press.

Martin, J. (2001). *Organizational culture: Mapping the terrain.* Sage Publications.

Martin, J., & Siehl, C. (1983). Organizational culture and counterculture: An uneasy symbiosis. *Organizational Dynamics, 12*(2), 52-64.

Martin, J., Frost, P. J., & O'Neill, O. A. (2006). Organizational culture: Beyond struggles for intellectual dominance. *The handbook of organization studies*, 725-753.

Mayo, E., Roethlisberger, F., & Dickson, W. (1939). Management and the Worker. Cambridge, MA: Harvard University Press.

McDonald, R. P., & Ho, M. H. R. (2002). Principles and practice in reporting structural equation analyses. *Psychological Methods*, *7*, 64-82.

McDonald, R. P., & Marsh, H. W. (1990). Choosing a multivariate model: Noncentrality and goodness of fit. *Psychological Bulletin*, *107*(2), 247.

McGregor, D. (1960). The human side of enterprise. New York, NY: McGraw-Hill.

McIntosh, C. (2006). Rethinking fit assessment in structural equation modelling: A commentary and elaboration on Barrett (2007). *Personality and Individual Differences*, *42*(5), 859-867.

McKay, P. F., Avery, D. R., & Morris, M. A. (2008). Mean racial-ethnic differences in employee sales performance: The moderating role of diversity climate. *Personnel Psychology*, *61*(2), 349-374.

McKnight, P. E., McKnight, K. M., Sidani, S., & Figueredo, A. J. (2007). *Missing data: A gentle introduction*. New York: Guilford Press.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 415-444.

Meyer, A. D., Tsui, A. S., & Hinings, C. R. (1993). Configurational approaches to organizational analysis. *Academy of Management Journal, 36*(6), 1175-1195.

Meyer, H. H. (1968). Achievement motivation and industrial climates. *Organizational Climate*, 35-65.

Milliken, F. J., & Martins, L. L. (1996). Searching for common threads: Understanding the multiple effects of diversity in organizational groups. *Academy of Management Review*, *21*(2), 402-433.

Moran, E. T., & Volkwein, J. F. (1992). The cultural approach to the formation of organizational climate. *Human Relations*, *45*(1), 19-47.

Morgan, P. I., & Ogbonna, E. (2008). Subcultural dynamics in transformation: A multi-perspective study of healthcare professionals. *Human Relations*, *61*(1), 39-65.

Morgeson, F. P., & Hofmann, D. A. (1999). The structure and function of collective constructs: Implications for multilevel research and theory development. *Academy of Management Review*, *24*(2), 249-265.

Mueller, L., DaSilva, N., Townsend, J., & Tetrick, L. (1999). *An empirical evaluation of competing safety climate measurement models.* Paper presented at the annual meeting of the Society for Industrial and Organizational Psychology, Atlanta, GA.

Mulaik, S. A., James, L. R., Van Alstine, J., Bennett, N., Lind, S., & Stilwell, C. D. (1989). Evaluation of goodness-of-fit indices for structural equation models. *Psychological Bulletin*, *105*(3), 430.

Muthén, B. (2004). Latent variable analysis. *The Sage handbook of quantitative methodology for the social sciences* (pp. 345-368). Thousand Oaks, CA: Sage.

Muthén, B., & Muthén, L. K. (2000). Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research, 24*(6), 882-891.

Nahrgang, J. D., Morgeson, F. P., & Hofmann, D. A. (2007). *Predicting safety performance: A meta-analysis of safety and organizational constructs.* Paper presented at the Poster session presented at the 22nd annual conference of the society for industrial and organizational psychology, New York, NY.

Nahrgang, J. D., Morgeson, F. P., & Hofmann, D. A. (2011). Safety at work: A meta-analytic investigation of the link between job demands, job resources, burnout, engagement, and safety outcomes. *Journal of Applied Psychology, 96*(1), 71-94. doi:10.1037/a0021484

Newman, D. A., & Sin, H. P. (2007). How do missing data bias estimates of within-group agreement? Sensitivity of SDWG, CVWG, rWG (J), rWG (J), and ICC to systematic nonresponse. *Organizational Research Methods, 12*(1), 113-147 doi:10.1177/1094428106298969

Nunnally, J. (1978). *Psychometric methods*. New York: McGraw Hill.

Nunnally, J. C., Bernstein, I. H., & Berge, J. M. T. (1995). *Psychometric theory* (Vol. 226). New York: McGraw-Hill.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling, 14*(4), 535-569.

Ostroff, C., & Fulmer, C. A. (2014). *Variance as a construct: Understanding variability beyond the mean*: American Psychological Association.

Ostroff, C., Kinicki, A. J., & Muhammad, R. S. (2013). Organizational culture and climate. In N. W. Schmitt & S. Highhouse (Eds.), *Handbook of psychology, Vol. 12: I/O psychology* (pp. 565-593). New York: Wiley.

Ostroff, C., Kinicki, A. J., & Tamkins, M. M. (2003). *Organizational culture and climate.* Wiley Online Library.

Ostroff, C., & Schulte, M. (2014). A Configural Approach to the Study of Organizational Culture and Climate. In B. Schneider & K. M. Barbera (Eds.), *The Oxford handbook of organizational climate and culture*, (pp. 532-552). New York, NY: Oxford University Press. doi: 10.1093/oxfordhb/9780199860715.013.0027

Owens, W. A., & Schoenfeldt, L. F. (1979). Toward a classification of persons. *Journal of Applied Psychology, 64*(5), 569.

Patterson, M. G., West, M. A., Shackleton, V. J., Dawson, J. F., Lawthom, R., Maitlis, S., Wallace, A. M. (2005). Validating the organizational climate measure: Links to managerial practices, productivity and innovation. *Journal of Organizational Behavior, 26*(4), 379-408.

Patterson, M., Payne, R., & West, M. (1996). Collective climates: A test of their sociopsychological significance. *Academy of Management Journal, 39*(6), 1675-1691.

Payne, G. T. (2006). Examining configurations and firm performance in a suboptimal equifinality context. *Organization Science, 17*(6), 756-770.

Payne, R. (1990). Madness in our method. A comment on Jackofsky and Slocum's paper, 'A longitudinal study of climates'. *Journal of Organizational Behavior, 11*(1), 77-80.

Payne, R., Fineman, S., & Wall, T. (1976). Organizational climate and job satisfaction: A conceptual synthesis. *Organizational Behavior and Human Performance, 16*(1), 45-62.

Pelled, L. H., Eisenhardt, K. M., & Xin, K. R. (1999). Exploring the black box: An analysis of work group diversity, conflict and performance. *Administrative Science Quarterly, 44*(1), 1-28.

Pettigrew, A. M. (1979). On studying organizational cultures. *Administrative Science Quarterly*, 570-581.

Pickett, C. L., & Brewer, M. B. (2001). Assimilation and differentiation needs as motivational determinants of perceived in-group and out-group homogeneity. *Journal of Experimental Social Psychology, 37*(4), 341-348.

Pirola-Merlo, A., Härtel, C., Mann, L., & Hirst, G. (2002). How leaders influence the impact of affective events on team climate and performance in R&D teams. *The Leadership Quarterly, 13*(5), 561-581.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879.

Probst, T. M. (2004). Safety and insecurity: Exploring the moderating effect of organizational safety climate. *Journal of Occupational Health Psychology, 9*(1), 3-10. doi:10.1037/1076-8998.9.1.3

Quinn, R. E., & Rohrbaugh, J. (1983). A spatial model of effectiveness criteria: Towards a competing values approach to organizational analysis. *Management Science*, *29*(3), 363-377.

Raykov, T., & Marcoulides, G. A. (2000). A method for comparing completely standardized solutions in multiple groups. *Structural Equation Modeling*, *7*(2), 292-308.

Rentsch, J. R. (1990). Climate and culture: Interaction and qualitative differences in organizational meanings. *Journal of Applied Psychology*, *75*(6), 668.

Roberson, Q. M., & Colquitt, J. A. (2005). Shared and configural justice: A social network model of justice in teams. *Academy of Management Review*, *30*(3), 595-607.

Roethlisberger, F. J. (1941). The Hawthorne Experiments. *Classics of Organizational Behaviour.* Interstate Printers, Danville, IL.

Satorra, A. B., & Bentler, P. M. (1994). Corrections to test statistics and standard errors in covariance structure analysis. *Latent variables analysis: Applications for developmental research*, 399-419.

Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods*, *7*(2), 147.

Schein, E. (1965). Organizational Psychology. Foundations of Modern Psychology series. Englewood Cliffs, NJ: Prentice-Hall.

Schein, E. H. (2010). *Organizational culture and leadership* (Vol. 2). John Wiley & Sons.

Schneider, B. (1975). Organizational climates: An essay. *Personnel Psychology, 28*(4), 447-479.

Schneider, B. (2000). The psychological life of organizations. In N. M. Ashkanasy, C. P. M. Wilderom and M. F. Peterson (Eds.), *Handbook of Organizational Culture and Climate*. Thousand Oaks, CA: Sage Publications.

Schneider, B., & Barbera, K. M. (2014). *The Oxford handbook of organizational climate and culture*. New York, NY, US: Oxford University Press. doi:10.1093/oxfordhb/9780199860715.001.0001

Schneider, B., & Bartlett, C. (1970). Individual differences and organizational climate ii: Measurement of organizational climate by the multi-trait, multi-rater matrix. *Personnel Psychology, 23*(4), 493-512.

Schneider, B., & Bartlett, C. J. (1968). Individual differences and organizational climate: The research plan and questionnaire development. *Personnel Psychology, 21*(3), 323-333.

Schneider, B., & Reichers, A. E. (1983). On the etiology of climates. *Personnel Psychology, 36*(1), 19-39.

Schneider, B., & Snyder, R. A. (1975). Some relationships between job satisfaction and organization climate. *Journal of Applied Psychology, 60*(3), 318.

Schneider, B., Ehrhart, M. G., & Macey, W. H. (2011). Perspectives on organizational climate and culture. In S. Zedeck, S. Zedeck (Eds.), *APA handbook of industrial and organizational psychology, Vol 1: Building and developing the organization* (pp. 373-414). Washington, DC, US: American Psychological Association. doi:10.1037/12169-01

Schneider, B., Ehrhart, M. G., & Macey, W. H. (2013). Organizational climate and culture. *Annual Review of Psychology, 64*, 361-388.

Schneider, B., Parkington, J. J., & Buxton, V. M. (1980). Employee and customer perceptions of service in banks. *Administrative Science Quarterly*, 252-267.

Schneider, B., Salvaggio, A. N., & Subirats, M. (2002). Climate strength: A new direction for climate research. *Journal of Applied Psychology, 87*(2), 220.

Schulte, M., Ostroff, C., & Kinicki, A. J. (2006). Organizational climate systems and psychological climate perceptions: A cross-level study of climate-satisfaction relationships. *Journal of Occupational and Organizational Psychology, 79*(4), 645-671.

Schulte, M., Ostroff, C., Shmulyian, S., & Kinicki, A. (2009). Organizational climate configurations: Relationships to collective attitudes, customer satisfaction, and financial performance. *Journal of Applied Psychology, 94*(3), 618.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6*(2), 461-464.

Scott, T., Mannion, R., Davies, H. T., & Marshall, M. N. (2003). Implementing culture change in health care: Theory and practice. *International Journal for Quality in Health Care, 15*(2), 111-118.

Simons, T. (2002). Behavioral integrity: The perceived alignment between managers' words and deeds as a research focus. *Organization Science, 13*(1), 18-35.

Steiger, J. H. (2007). Understanding the limitations of global fit assessment in structural equation modeling. *Personality and Individual Differences, 42*(5), 893-898.

Steiger, J. H., & Lind, J. C. (1980, May). Statistically based tests for the number of common factors. In *Annual meeting of the Psychometric Society, Iowa City, IA,* 758, 424-453.

Stryker, S. (1980). *Symbolic interactionism: A social structural version.* Benjamin-Cummings Publishing Company.

Tabachnick, B. G., & Fidell, L. S. (1989). *Using multivariate statistics.* New York, NY: Harper & Row.

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics.* Needham Height, MA: Allyn & Bacon.

Tagiuri, R. (1968). The concept of organizational climate. *Organizational climate: Exploration of a concept*, 11-32.

Tanaka, J. S. (1993). Multifaceted conceptions of fit in structural equation models. In K. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 10-39). Newbury Park, CA: Sage Publications.

Thompson, B. (2007). Effect sizes, confidence intervals, and confidence intervals for effect sizes. *Psychology in the Schools*, *44*(5), 423-432.

Trice, H. M., & Beyer, J. M. (1993). *The cultures of work organizations.* Englewood Cliffs, NJ: Prentice Hall.

Tsui, A. S., Egan, T. D., & O'Reilly, C. A., III (1992). Being different: Relational demography and organizational attachment. *Administrative Science Quarterly*, 549-579.

Tsui, A. S., Wang, H., & Xin, K. R. (2006). Organizational culture in China: An analysis of culture dimensions and culture types. *Management and Organization Review, 2*(3), 345-376.

Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika, 38*(1), 1-10.

Van Knippenberg, D., De Dreu, C. K., & Homan, A. C. (2004). Work group diversity and group performance: An integrative model and research agenda. *Journal of Applied Psychology, 89*(6), 1008.

Van Maanen, J., & Barley, S. R. (1985). *Cultural organization: Fragments of a theory.* Beverly Hills, CA: Sage Publications.

Vermunt, J. K., & Magidson, J. (2000). Latent Gold user's guide. *Belmont, MA: Statistical Innovations Inc.*

Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. *Applied Latent Class Analysis, 11*, 89-106.

Wallace, C., & Chen, G. (2006). A multilevel integration of personality, climate, self-regulation, and performance. *Personnel Psychology, 59*(3), 529-557. doi:10.1111/j.1744-6570.2006.00046.x

Wang, M., & Hanges, P. J. (2011). Latent class procedures: Applications to organizational research. *Organizational Research Methods, 14*(1), 24-31.

Weber, M. (1947). The theory of social and economic organization. In A. H. Henderson and T. Parsons, (Eds.), *The theory of social and economic organization.* Glencoe, IL: Free Press.

Weick, K. E. (1979). Cognitive processes in organizations. *Research in Organizational Behavior, 1*(1), 41-74.

Weick, K. E. (1993). The collapse of sensemaking in organizations: The Mann Gulch disaster. *Administrative Science Quarterly*, 628-652.

Weick, K. E. (1995). *Sensemaking in organizations* (Vol. 3). Sage.

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. *Organization Science, 16*(4), 409-421.

West, M. A., Topakas, A., & Dawson, J. F. (2014). Climate and culture for health care. In B. Schneider and K. M. Barbera (Eds.), *The Oxford handbook of organizational climate and culture* (pp. 335-359). New York, NY: Oxford University Press.

West, M., & Spendlove, M. (2006). The impact of culture and climate in healthcare organisations. In J. Cox, J. King, A. Hutchinson, and P. McAvoy (Eds.), *Understanding doctors' performance* (pp. 91-105). Seattle, WA: Radcliffe.

West, S. G., Finch, J. F., & Curran, P. J. (1995). Structural equation models with non-normal variables: Problems and remedies. In R. Hoyle (Ed.), *Structural Equation Modeling: Concepts, Issues and Applications*, (pp. 56-75). Newbury Park, CA: Sage.

Williams, K. Y., & O'Reilly, C. A., III (1998). A review of 40 years of research. *Research in Organizational Behavior, 20*, 77-140.

Wolfe, J. H. (1970). Pattern clustering by multivariate mixture analysis. *Multivariate Behavioral Research, 5*(3), 329-350.

Yuan, K. H. (2005). Fit indices versus test statistics. *Multivariate Behavioral Research, 40*, 115–148.

Zohar, D. (1980). Safety climate in industrial organizations: Theoretical and applied implications. *Journal of Applied Psychology, 65*(1), 96-102.

Zohar, D. (2000). A group-level model of safety climate: Testing the effect of group climate on microaccidents in manufacturing jobs. *Journal of Applied Psychology, 85*(4), 587-596.

Zohar, D. (2003). Safety climate: Conceptual and measurement issues. In J. C. Quick & L. E. Tetrick (Eds.), *Handbook of Occupational Health Psychology,* (pp. 123-142). Washington, DC, US: American Psychological Association. doi.org/10.1037/10474-006

Zohar, D. (2010). Thirty years of safety climate research: Reflections and future directions. *Accident Analysis & Prevention, 42*(5), 1517-1522. doi:10.1016/j.aap.2009.12.019 doi:10.1016/j.aap.2009.12.019

Zohar, D., & Hofmann, D. (2012). Organizational climate and culture. *The Oxford handbook of industrial and organizational psychology, 1*, 643-666.

Zohar, D., & Luria, G. (2004). Climate as a social-cognitive construction of supervisory safety practices: Scripts as proxy of behavior patterns. *Journal of Applied Psychology, 89*(2), 322.

Zohar, D., & Luria, G. (2005). A multilevel model of safety climate: Cross-level relationships between organization and group-level climates. *Journal of Applied Psychology, 90*(4), 616-628. doi:10.1037/0021-9010.90.4.616

Zohar, D., & Tenne-Gazit, O. (2008). Transformational leadership and group interaction as climate antecedents: A social network analysis. *Journal of Applied Psychology, 93*(4), 744-757. doi:10.1037/0021-9010.93.4.744

APPENDIX A
PERMISSION FOR SCALE USE

From: Dov Zohar
Date: March 8, 2014 at 0:43:47 CST
To: "Frost, Amy"
Subject: Re: Request permission for scale use
Dear Amy
You are welcome to use my scale as published in the Appendix of the JAP (2005) paper. I am away from my office now and have no access to the full RF scale. Please remind me to send the full scale by the end of March upon my return back home.
As I understand, your company is a global certification and verification company. If this is true, it might be possible to explore possible collaboration between us. For example, we may consider development (and validation) of industry-specific safety
climate scales you may subsequently use as proprietary scales for certification purposes. For example, I have recently developed with US colleagues a safety climate scale for truck drivers and tested its predictive validity using subsequent traffic injuries as outcome criterion. The new scale explained twice the injury variance by comparison with my generic scale (i,e, the JAP 2005 scale).
I'd be happy to explore such possibilities with you and your colleagues.
All the best and good luck with your thesis,
Dov
****
Professor Dov Zohar
Faculty of IE & Management
Technion Institute of Technology
Haifa 32000, ISRAEL

(O) 972-4-829-4440
(F) 972-4 829-5688
(C) 972-525-206064

APPENDIX B
DEMOGRAPHIC ITEMS

1. Which designation most closely matches your job function?
2. What is your age?
3. What is your highest level of education?
4. How long have you worked for this organization?

Organization-Level Safety Climate (Zohar & Luria, 2005)

Top management in this organization . . .

1. Reacts quickly to solve the problem when told about safety hazards.
2. Insists on thorough and regular safety audits and inspections.
3. Tries to continually improve safety levels in each department.
4. Provides all the equipment needed to do the job safely.
5. Is strict about working safely when work falls behind schedule.
6. Quickly corrects any safety hazard (even if it's costly).
7. Provides detailed safety reports to workers (e.g., injuries, near accidents).
8. Considers a person's safety behavior when moving–promoting people.
9. Requires each manager to help improve safety in his– her department.
10. Invests a lot of time and money in safety training for workers.
11. Uses any available information to improve existing safety rules.
12. Listens carefully to workers' ideas about improving safety.
13. Considers safety when setting production speed and schedules.
14. Provides workers with a lot of information on safety issues.
15. Regularly holds safety-awareness events (e.g., presentations, ceremonies).

APPENDIX C
WITHIN-SUBCLIMATE AGREEMENT

Within-subclimate Agreement

	Subclimate	N	$r_{wg(j)}$
rwgj_un	1	42	.8357
	2	140	.8854
	3	188	.8947
	4	61	.8152
	5	658	.9277