Chapter 6

GROUP CONFLICT AS AN EMERGENT STATE: TEMPORAL ISSUES IN THE CONCEPTUALIZATION AND MEASUREMENT OF DISAGREEMENT

Gerardo A. Okhuysen and Hettie A. Richardson

ABSTRACT

In this chapter, we suggest conflict in groups can be usefully examined as an emergent state, a construct that is dynamic in nature and varies as a function of members' interactions. Using the literature on emergent social processes, conflict, and groups as dynamic systems, we propose that emergent constructs must possess four characteristics: stability of meaning, variability over time, variability among groups that differ on other meaningful variables, and variation in consensus. Using data from 52 four-person student groups, we perform a series of tests to conclude that conceptualizing conflict as an emergent state is appropriate, and we consider the implications of such distinctions.

INTRODUCTION

The study of conflict in groups has advanced considerably over the past decade, driven by a desire to understand groups in a more fundamental manner and by a practical interest in helping groups become more effective. Although interest in and research on conflict in groups has advanced, there are many outstanding debates. For
example, some findings and conclusions regarding conflict in groups are contradictory (De Dreu and Weingart, 2003), while other findings are complex and difficult to understand (Mannix and Jehn, 2004). These difficulties have been attributed to a variety of shortcomings. For instance, the psychometric properties of scales used to measure conflict have been subject to debate, leading to their refinement (Pearson, Ensley, and Amason, 2002). Theoretical distinctions, such as those between task conflict and process conflict or between conflict and emotion (Jehn and Bendersky, 2003), have also been noted as difficulties in the study of conflict.

An important—yet less remarked on—obstacle to pursuing a deeper understanding of the role conflict plays in groups is the gap that exists concerning how conflict is experienced by members of a group, how it is conceptualized theoretically, and how it is operationalized in our research. Specifically, although conflict is widely acknowledged as a dynamic element of groups, and although it is understood to be the result of the ongoing interactions among group members, most studies that examine it have used a single-point measure of the phenomenon, implicitly treating conflict as a stable and static property of groups. Take, for example, examinations of the link between task conflict and performance in a problem-solving or decision-making team. Jehn (1995) suggested that task conflict and performance have a positive relationship because groups with task conflict air their differences of opinion on their work openly. This open discussion, in turn, is supposed to result in better performance as members find better ways to execute their work. Subsequent work has sometimes supported, sometimes contradicted, and sometimes rejected this hypothesis (De Dreu and Weingart, 2003). These findings, though, are largely based on single-point measures of conflict.

In this chapter, we propose two related and complementary ideas. First, we suggest that single-point measures of dynamic elements such as conflict may present a host of difficulties. Consider a straightforward example using task conflict and performance, a case in which a group is unsure of what its task is at the outset of its activities, leading to an active discussion of the task among members. As the task is defined by members, suppose consensus develops, decreasing disagreement and the need for additional discussion, and that this move toward consensus is reflected in a linear decrease in the reported amount of task conflict. Assume, furthermore, that this group performs well. If conflict is measured a single time at the beginning of this group's work, higher task conflict will be related to good performance. However, if conflict is measured at the midpoint in the group's life, a moderate level of task conflict will be related to good performance. As should be evident, if conflict is measured at the end of the group's activities, low task conflict will be related to good performance. Thus, the timing of measurement in any single study might influence the relationship found between a dynamic variable (such as conflict) and a final outcome (such as group performance). Not surprisingly, this type of finding also will be difficult to replicate, as other data sets may incorporate their own (and different) timing properties. As a possible example of the difficulty of replication, De Dreu and
Weingart (2003), in a meta-analysis examining the associations among relationship conflict, task conflict, performance, and satisfaction, conclude that no positive relationship exists between task conflict and performance.

We recognize the difficulty of examining dynamic constructs using single-point measures, and in examining these dynamic properties we rely in this chapter on recent theoretical treatments of groups as dynamic systems. This literature suggests our understanding of groups would be strengthened by an incorporation of dynamic conceptualizations, language, and constructs into our work (Arrow, McGrath, and Berdahl, 2000). However, little work has attempted to translate this theoretical understanding into empirical practice. We suggest that an appropriate strategy for investigating conflict is to conceptualize it as an emergent state, a property of a group that results from interactions among group members and that can provide the group both with structure (Margeson and Hofmann, 1999) and with dynamic properties that vary depending on members' activities (Marks, Mathieu, and Zaccaro, 2001). We first present a brief literature background on conflict in groups and on groups as complex systems. We then articulate four conceptual and empirical properties of emergent constructs and examine conflict from the perspective of these properties. In particular, we focus on four characteristics of dynamic constructs. These include stability of meaning, or a consistency in interpretation; variability over time, or an ability to capture differences; variability among groups that differ on other meaningful variables, or a predictive ability; and variation in consensus, or an ability to capture emergent concurrence. Using data from 52 student groups working on a semester-long project, we use our analyses to explore the properties of relationship, task, and process conflict as emergent states. Finally, we consider the implications of our findings.

BACKGROUND

THE ROOTS OF CONFLICT

Conflict is typically defined as a discrepancy in perceptions or understandings among group members that can be related to several issues in the group (De Dreu and Weingart, 2003; Jehn, 1997; Jehn and Mannix, 2001). Relationship conflict, for example, comes from interpersonal difficulties, whether these derive from differences in political values or simply a general dislike of one another. Relationship conflict at high levels can be reflected in emotional displays, such as anger or frustration. Task conflict is a difference in perspectives related to the work of the group, about what is to be done, and is a discrepancy of ideas and opinions. Finally, process conflict is related to issues of coordination, about how the work is to be done. It is important to note the literature considers conflict to be the expression of these discrepancies. In other words, if individuals subsume their differences, either in the
interest of a relationship or task or because the differences are not considered important, then conflict is understood to be lessened, even if the discrepancies in perspectives remain.

Over time, research has changed its perspective on the value of conflict (Jehn and Bendersky, 2003) from having a consistently negative evaluation of the role of conflict in groups (e.g., Hackman and Morris, 1975) to current perspectives that suggest conflict can have some positive outcomes (for example, Amason, 1996; Jehn, 1995). In particular, research that examines the expression of authentic conflict (Nemeth, Connell, Rogers, and Brown, 2001) and the introduction of task conflict into groups through the use of a devil's advocate has suggested that conflict may improve the quality of decision making (Amason, 1996; Eisenhardt, 1989). The exploration of the potentially positive outcomes of conflict is rooted in a belief that passive, accommodating, and consensus-driven teams do not always engage in careful analysis of alternatives for decisions (Eisenhardt, 1989; Nemeth et al., 2001).

**Dynamic Elements in Groups**

Conceptualizations of conflict have always had at their core a characterization of conflict as a dynamic variable in the group. As such, attention to conflict has responded to a consistent drumbeat calling for a focus on process as an explanatory element of group activity (Hackman and Morris, 1975; Marks et al., 2001) that goes hand in hand with calls for longitudinal explorations of group phenomena (Marks et al., 2001; McGrath, 1984). This focus on dynamic elements, however, has been restricted by the use of cross-sectional designs that reflect an input/output perspective, albeit with process measures taking the role of inputs into the group. As such, constructs reflecting group dynamics often have been operationalized as static properties (Jehn and Mannix, 2001). Although this approach has been beneficial and has substantially advanced our thinking about various group processes, it is also problematic because it cannot always reflect the real-life group phenomena that it attempts to characterize. Although there is still considerable room for the exploration of groups using cross-sectional methods that assume some degree of stability in the group, it is also clear that researchers must begin to engage groups as they are—that is, as entities with dynamic elements. Recent advances in our thinking on the dynamic nature of groups (and other social systems) are useful in suggesting how we might proceed in such an examination from a theoretical point of view.

**Dynamic Approaches to Understanding Groups**

The focus on groups as dynamic systems is not new. For example, a research team led by Joseph McGrath (1993) collected voluminous data from student groups working on a variety of tasks during two semesters. These studies (labeled JEMCO 1 and
JEMCO 2) were quite ambitious and insightful, but they also pointed to the problems that appear when using dynamic perspectives to study groups. These difficulties are best described by some of the researchers themselves; for example, Arrow et al., (2000, p. 276) suggest that consideration of groups as dynamic systems provides results that are “too complicated for definitive analysis.” These researchers similarly note the difficulty with standard study designs for these groups, because “[n]o one design is satisfactory in all respects.” As the authors explain, the JEMCO studies suffered from their ambition, with perhaps an excessive number of objectives for phenomena they tried to explain (which ranged from the effects of communication media and membership change to the effects of different tasks on the group).

Although these early examinations of groups as dynamic systems pointed to difficulties, recent developments in our conceptualization of social processes may be helpful in guiding us to more general theoretical approaches, while also providing specificity for operationalizing research. In particular, recent progress in how we conceptualize social systems can help us simplify a dynamic approach and, at the same time, allow us to gain a more complete understanding of the elements that make up a dynamic system. One useful perspective is the elaboration of collective constructs (Morgeson and Hofmann, 1999) that reflect phenomena emerging from the interactions of lower-level entities and that can provide structure for subsequent interactions. In addition, a recent emphasis on time and temporal issues has provided important insights and tools for examining dynamic social systems. Zaheer, Albert, and Zaheer (1999) describe how the use of timescales (time intervals of different lengths) forces us to clearly specify the time period over which phenomena take place, helping us advance our understanding of organizational processes through better theory development and specification. Timescales help us understand dynamic systems by providing us with a means to distinguish between variables that change at different rates, such as group norms and group emotion. Similarly, Marks et al. (2001) propose a taxonomy of group process that uses the episodic nature of group activity as a centerpiece. These episodes of activity can simultaneously account for the multitasking nature of the group and for the changing nature of group elements through growth or decay. Finally, Arrow et al. (2000), learning from the JEMCO studies, propose a complete framework for examining groups as complex systems. Their detailed treatment of different pressures (internal and external, individual and group, task and process) highlights how elements within groups can be differentiated when they are examined through a lens that accounts for their dynamic properties.

A particularly useful contribution from the work on dynamic social systems has come from characterizations of different types of dynamic elements and the properties they possess. For example, authors have attempted to characterize processes, attractors, and emergent states in a detailed manner. Marks et al. (2001, p. 357), for instance, reserve the label of group “process” for “members’ interdependent acts . . . to achieve collective goals.” Thus, the focus is principally on process as task-oriented interdependent action. Arrow et al. (2000, p. 41) define “attractors” as regions where
variables "settle into certain values." These attractors can "affect the overall trajectory" of groups and include properties of groups that are stable across longer timescales. Examples might include norms such as "group value consensus," the extent to which members agree on underlying organizing values (Jehn and Mannix, 2001). A third type of dynamic property is an "emergent state," a property of the group that is "typically dynamic in nature and [varies] as a function of team context, inputs, processes, and outcomes" (Marks et al., 2001, p. 357). Emergent states have "mutable qualities" that are "fluid and more easily influenced by context" (Marks et al., 2001, p. 358).

This theoretical differentiation between types of dynamic elements in groups is valuable because it gives us the tools to explicitly consider questions of timescales and stability. However, these advances in our theoretical understanding also have created a need for empirical specification of the different types of dynamic elements. In the next section, we attempt to characterize the empirical properties of emergent states in general and of conflict as an emergent state in particular.

**EMERGENCE AS A PROPERTY OF GROUPS**

Emergence is typically understood as a property that smaller or simpler entities generate when they are aggregated into a collective (Holland, 1998). Some typical examples are neurons aggregated into the brain, transactions aggregated into markets, and so on. A central characteristic of emergence is that the aggregation of the activities of the lower-level (and simpler) units forms a more complex entity at a higher level (Holland, 1998). For groups, emergence results from the interactions among individuals, and it is from these interactions that group-level phenomena arise.

Although groups themselves can be characterized by emergence, not all properties of groups (as studied in the literature) are the result of emergence. Thus, for example, the demographic characteristics of a group do not rely on the interactions among members, but rather depend on the pre-existing characteristics of members. However, other elements of group life are amenable to being viewed through an emergence lens. For example, those studying the broad field of diversity rely on arguments of emergence to understand how group members' differences affect the processes and outcomes of groups. The appearance of faultlines (Lau and Murnighan, 1998), for instance, is a good example of emergence in groups. The composition of the group sets the initial condition for the faultlines, but it is the interactions among members that create the consequences from the initial conditions. A similar example comes from work on deep-level diversity (Harrison, Price, Gavin, and Florey, 2002; Harrison, Price, and Bell, 1998), which shows that as interactions take place, visible demographic characteristics become less important. Instead, underlying similarities among group members (in attitudes toward work, for example) become more important to those attempting to understand their behavior.
The examples of faultlines and deep-level diversity in groups point to another element that is critical to understanding emergence in groups: the relevance of timescales. In groups, multiple phenomena coexist in a wide variety of temporal arrangements. Some of the phenomena, such as the impact of visible diversity on interactions, can appear immediately upon formation of a group. However, the impact of other elements in the group, such as deep-level similarity or diversity, may have longer gestation periods due to the need to uncover and decipher the individual-level characteristics that constitute it. The differences between timescales become important in our thinking because, as research advances to explain group behavior, the temporal arrangements between phenomena will need to be explored.

Although the emphasis so far in the literature about this topic has been on the internal dynamics of the group, the notion of emergence can also account for influences from the environment on the group and for outputs from the group to the environment. This ability to account for interactions with the environment is important for us because groups are open systems (Gladstein, 1984), and they draw resources and experiences from the environments in which they operate. The environment can cause shocks to groups as well, through the provision of feedback, for example. In addition, groups also influence their environments through their actions and outputs.

As we noted earlier, characterizing dynamic elements in groups is problematic. Many of the instruments used to measure group phenomena—such as conflict—typically are designed to capture a snapshot of a given phenomenon at a single point or on average across a temporal period. For this reason, they are conceptually incongruent with capturing phenomena that are dynamic over varying time intervals. Although existing literature suggests what the properties of an emergent construct might be from a theoretical perspective, the properties of emergence from an empirical perspective are vague. In the following section, we describe four conceptual properties of constructs that attempt to capture emergent states and begin to address some of the empirical implications of those properties.

**Properties of an Emergent State**

One way researchers can use the concept of emergence to understand groups is to characterize elements in the group according to their emergent characteristics. We suggest that constructs that attempt to capture emergent states have four properties that are relevant for the constructs’ conceptual and empirical meaning. Specifically, the properties are (1) stability of meaning across time, individuals (within and between groups), and contextual influences; (2) true variability in level or intensity over time; (3) differences in patterns of variability among groups that differ on other meaningful variables; and (4) variation among group members in consensus regarding assessments of level or intensity.
Stability of meaning across time. First, an emergent state must be understood or comprehended in the same way over time such that there is "stability of meaning" in the construct being measured. Though emergent states are, by definition, dynamic and mutable, the underlying domain of a given emergent state should not be. Instead, the underlying conceptual domain of the emergent state—as understood by group members and the researcher alike—should remain constant over time. Conceptually, consistency is desirable because it pushes us toward parsimony. As we attempt to understand group phenomena, one challenge we face is trying to characterize similar—yet varied—incidents of social life. A desire for conceptual consistency forces us to carefully aggregate these incidents into an abstract construct while simultaneously fending off a tendency to consider phenomena together that might be distinct. Thus, though levels of the construct may change depending on when a measure is taken (for example, group members may experience high conflict today but low conflict tomorrow), actual understanding among group members and others about what conflict is should remain constant. Otherwise, there is the possibility that supposed assessments of a single proposed emergent state are in reality capturing two or more conceptually distinct group properties—even if, for instance, the same measurement instrument is used at both times.

Consider the example of relationship conflict. If the understanding of relationship conflict is mutable, rather than the perceptions about the presence or absence of relationship conflict in the group, then existing measurement techniques are not equipped to capture it as a dynamic construct. However, a consistent understanding of relationship conflict does not mean that group members necessarily agree with one another in their assessments of the presence, absence, or level of such conflict. Rather, consistent understanding implies that people conceptually think about relationship conflict in the same way (for example, as interpersonal difficulties)—regardless of time, group membership, individual differences, or other contextual influences. Such consistency ensures that, as scientists, we have successfully developed meaningful constructs that simplify group life while simultaneously acknowledging its complexity.

Variability over time. Morgeson and Hofmann (1999) argue that emergent properties appear and change as a function of social interaction. As group members develop recognition of the properties that characterize their group over time, emergent states appear. This developed recognition also implies that emergent states are not static but can change in intensity based on the nature and extent of member interaction. Thus, emergent states have the ability to change in level or value over an appropriate time scale, and we suggest that this variability is the second characteristic of an emergent construct. For groups, appropriate time scales can include a single performance episode, multiple performance episodes, or even the life of the group. More specifically, we argue that although a construct does not have to change in intensity over the life of a group, it must have the ability to do so within that time-scale if it is to be considered an emergent state. As such, measures of an emergent
construct must be able to capture differences in actual levels of the construct rather than, for example, differences in respondents' conceptualization of the construct (as noted earlier). The latter also means that, necessarily, an emergent construct cannot be adequately captured through single-point estimates.

**Difference in patterns of variability.** Margeson and Hofmann (1999, p. 254) also argued that emergent properties can be understood through their function, where function is defined as the causal outputs or effects of a given construct. If an emergent construct is to be useful in increasing understanding about groups, then we would expect patterns of emergence to vary among groups that also differ in other meaningful ways—such as among groups that have achieved different levels of performance on the same task. In other words, differences in patterns of emergent states across groups should be related to other meaningful differences across those groups. As such, we suggest that emergent states should be associated with certain outcomes. Although there should be consistency in how the emergent construct is understood across those outcomes (as per our first property of an emergent state), there also should be variability in the true levels and intensity of the construct across relevant outcomes. To illustrate, the theoretical function of relationship conflict suggests that different levels and rates of change in relationship conflict are likely to be associated with different levels of performance, even though low performers must understand relationship conflict in the same way as high performers do.

**Variation in consensus across time.** Finally, within the appropriate timescale, members are likely to exhibit varying degrees of within-group consensus regarding their assessments of the level or intensity of an emergent construct. For example, when a group is newly formed, when members have no prior experience with one another, and when members have interacted very little, it is less likely they will report similar levels of task conflict—for they have little common experience and interaction on which to base their assessments. On the other hand, as group members work together for longer periods of time, the group may develop characteristic levels of conflict, and members may become more consistent in their assessment of whether they are experiencing low or high levels of conflict. In addition, environmental shocks to the group—a change in membership, a change in task, or reassessment due to an approaching deadline—may cause group members to temporarily disagree regarding the experienced level of task conflict, until further group interactions allow new, consistent perceptions of task conflict to reemerge.

These changing levels of consensus are important because researchers typically rely on indices of rater consensus as criteria for justifying the aggregation of individual responses to the group level (Bliese, 2000). We suggest that the concept of emergent states implies that, depending on when a measure is taken, researchers should not necessarily expect group members to exhibit consensus about the level or intensity of a construct that is perceived. However, there should always be times at which group members exhibit strong consensus about the perceived intensity of an emergent state. In some instances, it also might be reasonable to expect a pattern
of consensus and disagreement to develop across performance episodes or in the face of recurring environmental shocks.

In the next section, we first describe the sample we used to examine the emergent properties of relationship conflict, task conflict, and process conflict. We follow this with descriptions of the analytical procedures and results.

SAMPLE AND METHODS

SAMPLE

The study was part of a 15-week-long introductory organizational behavior course in a public university in the southwestern United States. During the first week of class, the instructor randomly assigned four individuals to each of 52 groups. The average age of participants was 21 years, and the sample was 32 percent female. The task for the groups was an open-ended project in which the students conducted research on a specific organization to examine it through any one of the analytical frameworks learned in class. The final outcome of each group's work was a written report. Typical reports discussed chief executive officer (CEO) succession, financial fraud, employee selection practices, and so on. For the vast majority of the projects, this report entailed library archival research about a particular focal company. A few reports relied on interviews in addition to archival materials if students had access to individuals who worked or had worked for the focal company.

DATA COLLECTION

In the first week, individuals completed questionnaires regarding conflict in their groups immediately after their first in-class meeting. The questionnaire used Jehn's (1995) Intragroup Conflict Scale. This scale includes nine items and characterizes conflict as having three components: task conflict, relationship conflict, and process conflict. Individuals also completed this questionnaire in weeks 5, 9, and 13 of the 15-week semester. Response rates were relatively constant (around 95 percent) across all four data collection moments (see Table 6.1).

<table>
<thead>
<tr>
<th>Table 6.1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Response Rates per Week (n = 208)</strong></td>
</tr>
<tr>
<td>Week 1</td>
</tr>
<tr>
<td>Percent respondents</td>
</tr>
</tbody>
</table>
In addition to the data collected through questionnaires, we also collected performance data as the average grade awarded by two independent raters on the final written report. Each rater could award a maximum of 20 points for each report, and every group member received the same score. The two performance ratings were highly correlated, .73 (\( p = .001 \)). In no report was the difference in the number of points awarded greater than 2. (In 63 percent of the cases, there was only a 1-point difference, or no difference, in the scores awarded by the two raters.)

**ANALYTICAL PROCEDURES**

In this section, we describe the analytical procedures we used to test the three types of group conflict to determine the extent to which they exhibit the characteristics of an emergent state. For clarity of presentation, we divide the following discussion into four sections, with each representing the tests conducted for each characteristic of an emergent state: (1) consistent interpretation over time, or stability of meaning, (2) ability to change over time, or variability, (3) differences in patterns of variability among groups that differ on other meaningful variables, or predictive validity, and (4) variation in within-group consensus over time.

**Testing for Stability of Meaning across Time**

Following the procedure described by Chan (1998), we first examined the extent to which each conflict variable (that is, relationship conflict, task conflict, and process conflict) exhibited measurement invariance over time. In other words, we examined whether the three types of conflict exhibited evidence that respondents conceptualized conflict and the scales used to measure conflict differently across the four measurement occasions. These analyses specifically tested for the presence of beta and gamma change in the conflict constructs (Riordan, Richardson, Schaffer, and Vandenberg, 2001). Beta change occurs when respondents recalibrate the rating scale on which items comprising a given construct are measured such that differences in the construct scores actually represent altered interpretations of the rating-scale anchors. Gamma change occurs when respondents reconceptualize the domain of a construct between measurement occasions; this change essentially indicates that the construct being measured over time is not the same. If either beta or gamma change was present, we concluded group members did not have a consistent understanding of a given type of conflict between the beginning and end of the task activities. As such, the first criterion for an emergent state would not be met, and it would be impossible to examine that construct for true variability over time.

To establish measurement invariance over the four measurement occasions, we estimated a hierarchical series of five nested models (Chan, 1998) separately for each of the three types of conflict. Each model comprised four latent constructs, each representing a given conflict measure at times 1, 2, 3, and 4. Likewise, each of the four constructs was measured using the three associated items from the appropriate time...
period. The five models varied, however, in that each imposed increasing restrictions (i.e., equal factor loadings, error variances, factor means, and factor variances) on the estimated parameters across time. Support for equal factor loadings would be sufficient to establish measurement invariance over time. Support for equal error variances over time would provide a stricter test of measurement invariance. Nonetheless, when there are true changes in a construct over time, it is not unreasonable to expect error variances to differ as well—even for a truly invariant construct (Chan, 1998). Support for unequal factor means and variances would provide initial support for the following phase of analyses. Details regarding each model estimated can be found in appendix 6.A.

**Testing for Variability over Time**

Theoretically, relationship conflict, task conflict, and process conflict do have the ability to change over time. In this phase of analyses, however, we empirically tested whether they did change over time in our data. If they did, we examined their patterns of change. Specifically, we used latent growth modeling (LGM), again in a series of nested models for each construct separately. In this latter phase, three models were estimated for each construct: a no-growth model, a linear growth model, and a curvilinear or quadratic model. Detailed descriptions of these models also are found in appendix 6.A. Poor fit for the no-growth model combined with support for either the linear or quadratic models would provide evidence of the existence and nature of variability in level or intensity over time.

**Testing for Differences in Patterns of Variability**

The third property of an emergent state is that it exhibits differing patterns of emergence among groups that differ in some other meaningful way. In other words, all groups should not exhibit identical levels and rates of variability. Because researchers have proposed that conflict might be experienced differently by those who achieve differing levels of performance (Jehn and Mannix, 2001)—or that patterns of variability in conflict may be predictive of performance—we chose to examine the extent to which patterns of change in conflict across time varied between high performers and low performers. The median level of average performance (as rated by the two raters) was 16.00. Thus, we defined high-performing groups as those that earned an average performance score of 16.00 or better \( (n = 94) \) and low-performing groups as those that earned an average performance score of less than 16.00 \( (n = 71) \), after accounting for individuals with missing data. Individuals were assigned to the high- and low-performance designations based on their particular group's average performance.

For this phase of analyses, we estimated models that were similar to those in the previous step, but we modeled variability over time simultaneously for both high and low levels of performance. The purpose of these multigroup models was to fully determine if any significant differences existed in the patterns of change in the three
types of conflict between the high and low performers and, if so, what the nature of
the differences was. Prior to estimating multigroup LGM models, however, LGM
models identical to those estimated for the entire sample were analyzed for high and
low performers separately. The purpose of these models was to establish the shape of
change for each group of respondents. Provided the same shape was found for both
groups for a given type of conflict, it was appropriate to estimate the multigroup
LGM models for that type of conflict in order to test for subtler differences in rates
of and variance in change. If different shapes were found (for example, one linear,
one curvilinear), there was evidence that the pattern of change was fully different
between the groups and that multigroup analyses could not be estimated.

When multigroup LGM analyses were appropriate, seven additional models
were estimated in which intercept, slope, and quadratic factor means and variances
were successively constrained to be equal between high and low performers. If con­
straining a certain parameter to be equal between the groups produced significantly
worse fit in the data, then there was evidence that parameter was significantly differ­
ent for high and low performers. Again, details of the final seven models tested are
presented in appendix 6.A.

Testing for Variation in Consensus across Time
Intraclass correlation coefficient (ICC) values were used to examine the level of
within-group consensus of ratings for each type of conflict at each time period.
ICC(1) is a measure of the internal consistency, or interrelatedness, of ratings among
raters (Shrout and Fleiss, 1979). As such, it can be conceptualized as the extent to
which raters are substitutable for one another. It has also been suggested that ICC(1)
represents the proportion of total variance that can be explained by group mem­
bership (Bryk and Raudenbush, 1992). ICC(2) indicates the degree of agreement of
group members' ratings for each type of conflict. Once a construct has fully emerged
within a group and/or has reemerged following an environmental shock, we would
expect that group members' ratings of conflict would be substitutable for one anoth­
er and also that the ratings would more likely be a function of group membership
than of individual perceptions or differences. In this situation, we also would expect
group members to agree about the levels of conflict experienced within their groups.

RESULTS
Testing for Stability of Meaning across Time
Table 6.2 shows fit statistics and model comparison results for all five models estimat­
ed in order to examine the first property of emergent states: consistent conceptual­
ization across the entire sample, over time. All three types of conflict show evidence
of measurement invariance as indicated by a nonsignificant change in fit between the
unconstrained model and model 2. Further, because these analyses are at the individ­
ual level, the results not only indicate invariance over time but regardless of group
Table 6.2
Model Fit and Comparison for Determining Stability of Meaning across Time for the Entire Sample

<table>
<thead>
<tr>
<th>Model</th>
<th>$\chi^2$ (d.f.)</th>
<th>RMSEA</th>
<th>NNFI</th>
<th>CFI</th>
<th>Model Comparison</th>
<th>$\Delta \chi^2$ (d.f.)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Relationship conflict</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1: Unconstrained</td>
<td>47.45 (48)</td>
<td>.00</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 2: Equal factor loadings</td>
<td>48.80 (54)</td>
<td>.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1 versus 2</td>
<td>1.35 (6)</td>
</tr>
<tr>
<td>Model 3: Equal error variances</td>
<td>115.83* (63)</td>
<td>.07</td>
<td>.97</td>
<td>.97</td>
<td>2 versus 3</td>
<td>67.03* (9)</td>
</tr>
<tr>
<td>Model 4: Equal factor means</td>
<td>235.71* (57)</td>
<td>.11</td>
<td>.88</td>
<td>.90</td>
<td>2 versus 4</td>
<td>186.91* (3)</td>
</tr>
<tr>
<td>Model 5: Equal factor variances</td>
<td>181.72* (57)</td>
<td>.10</td>
<td>.92</td>
<td>.93</td>
<td>2 versus 5</td>
<td>132.92* (3)</td>
</tr>
<tr>
<td><strong>Task conflict</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1: Unconstrained</td>
<td>62.49 (48)</td>
<td>.05</td>
<td>.99</td>
<td>.99</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 2: Equal factor loadings</td>
<td>68.37 (54)</td>
<td>.05</td>
<td>.99</td>
<td>.99</td>
<td>1 versus 2</td>
<td>5.88 (6)</td>
</tr>
<tr>
<td>Model 3: Equal error variances</td>
<td>228.88* (63)</td>
<td>.13</td>
<td>.92</td>
<td>.92</td>
<td>2 versus 3</td>
<td>160.51* (9)</td>
</tr>
<tr>
<td>Model 4: Equal factor means</td>
<td>170.81* (57)</td>
<td>.10</td>
<td>.94</td>
<td>.95</td>
<td>2 versus 4</td>
<td>102.44* (3)</td>
</tr>
<tr>
<td>Model 5: Equal factor variances</td>
<td>124.70* (57)</td>
<td>.08</td>
<td>.96</td>
<td>.97</td>
<td>2 versus 5</td>
<td>56.33* (3)</td>
</tr>
<tr>
<td><strong>Process conflict</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1: Unconstrained</td>
<td>53.73 (48)</td>
<td>.02</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 2: Equal factor loadings</td>
<td>57.98 (54)</td>
<td>.02</td>
<td>1.00</td>
<td>1.00</td>
<td>1 versus 2</td>
<td>4.25 (6)</td>
</tr>
<tr>
<td>Model 3: Equal error variances</td>
<td>131.70* (63)</td>
<td>.09</td>
<td>.96</td>
<td>.97</td>
<td>2 versus 3</td>
<td>73.72* (9)</td>
</tr>
<tr>
<td>Model 4: Equal factor means</td>
<td>136.39* (57)</td>
<td>.09</td>
<td>.95</td>
<td>.96</td>
<td>2 versus 4</td>
<td>78.41* (3)</td>
</tr>
<tr>
<td>Model 5: Equal factor variances</td>
<td>133.83* (57)</td>
<td>.08</td>
<td>.96</td>
<td>.96</td>
<td>2 versus 5</td>
<td>75.85* (3)</td>
</tr>
</tbody>
</table>

* $p \leq .05$
Due to its superior fit, the second model was retained for comparison with model 3 in all cases. Likewise, across all three types of conflict, the second model fit significantly better than models 3, 4, and 5. The significant decrease in fit between the second and third models suggests that the error variances within type of conflict are not equal across time, and, according to Chan (1998), differences in true variance across time exist. The significant decrease in fit between the second and fourth models indicates that factor means for each type of conflict are not equal over time. As such, there is further evidence that significant true intraindividual change occurs within the data, and it is appropriate to model latent growth for each type of conflict.

Before considering the differences between models 2 and 5, it is first worthwhile to examine the latent factor means for each type of conflict as established in model 2. Changes in latent factor means are presented in graphic form in Figure 6.1, and the actual factor means at each measurement occasion are shown in Table 6.3. Note that, for the changes in means shown in Figure 6.1, time 1 means are set to a value of 0, such that the mean value at each of the remaining measurement occasions represents the difference in value between that time period and time 1. As illustrated, the general trend among all three types of conflict is for possible quadratic, rather than simply linear, change. For both relationship conflict and process conflict, responses exhibit a positive linear trend in the earlier measurement periods before decreasing in conflict by time 4. For process conflict, responses decrease to a level similar to their initial level by time 4, whereas for relationship conflict the final level remains greater than the initial level reported. Unlike with relationship conflict and process conflict, task conflict responses decrease in magnitude across all four measurement periods—although the rate of decrease appears to lessen slightly between times 3 and 4.

Finally, the significant difference between the second and fifth models across all three types of conflict indicates that factor variances for each are not equal across time. According to Chan (1998), factor variances reflect interindividual differences in true scores over time. For relationship conflict, factor variances are .40, 1.22, 1.57, and 3.17 for times 1 through 4, respectively. Task conflict variances are .89, 2.13, 2.55, and 2.30. Process conflict variances are 1.01, 2.06, 3.26, and 4.43. Factor covariances for all three types of conflict are positive and statistically significant at $p = .05$. These patterns of variances generally suggest that, at time 1, individuals have similar origins (as might be expected, given that they were all members of newly formed groups) but experience all three types of conflict differently over time. Change over time is confirmed and the precise nature of the growth curves established, however, in the following analyses.

**Testing for Variability over Time**

Table 6.4 shows fit statistics and model comparison results for the three latent growth models estimated for each type of conflict. The table also presents some key param-
eters estimated in models 2 and 3 for each of the three conflict variables. For all three types of conflict, model 2 fit significantly better than model 1, indicating that some form of growth is likely and that it is appropriate to examine models 2 and 3. In all cases, the third model also fit significantly better than the second model, indicating that the growth is not simply linear in nature but is, in fact, quadratic. Quadratic growth implies that the growth changes direction at some point in time—that there are paths of both acceleration and deceleration for each type of conflict. This finding largely confirms the pattern of factor means graphed in Figure 6.1.

Given that model 3 is always the superior-fitting model in our data, it is useful to specifically consider the factor means and variances of the second-order intercept, slope, and quadratic factors (also shown in Table 6.4) for each type of conflict. In all cases, the intercept mean value represents the average intercept as estimated from the individual intercepts across the entire sample, and the intercept variance represents variability in individual intercepts about the average estimated intercept. Similarly, the slope mean value is the average estimated slope (or growth trajectory) for a given type of conflict across time, and the slope variance is the average variability in slope. Finally, the quadratic mean value represents the average decelerating component of the growth trajectory for relationship conflict and process conflict and the average accelerating trajectory for task conflict. Again, the quadratic variance indicates variability in the quadratic component.
Table 6.3
Actual Latent Factor Means for the Entire Sample and for High and Low Performers Separately

<table>
<thead>
<tr>
<th>Conflict Type</th>
<th>Time 1</th>
<th></th>
<th></th>
<th>Time 2</th>
<th></th>
<th></th>
<th>Time 3</th>
<th></th>
<th></th>
<th>Time 4</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>High</td>
<td>Low</td>
<td>All</td>
<td>High</td>
<td>Low</td>
<td>All</td>
<td>High</td>
<td>Low</td>
<td>All</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Relationship</td>
<td>1.95</td>
<td>1.96</td>
<td>1.94</td>
<td>2.56</td>
<td>2.26</td>
<td>2.89</td>
<td>3.43</td>
<td>3.17</td>
<td>3.73</td>
<td>3.07</td>
<td>2.63</td>
<td>3.58</td>
</tr>
<tr>
<td>Task</td>
<td>3.96</td>
<td>4.06</td>
<td>3.86</td>
<td>3.37</td>
<td>3.31</td>
<td>3.44</td>
<td>2.85</td>
<td>2.67</td>
<td>3.05</td>
<td>2.57</td>
<td>2.54</td>
<td>2.61</td>
</tr>
<tr>
<td>Relationship Conflict</td>
<td>Model 1: No growth</td>
<td>Model 2: Linear</td>
<td>Model 3: Quadratic</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-----------------------</td>
<td>-------------------</td>
<td>----------------</td>
<td>-------------------</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\chi^2$ (d.f.)</td>
<td>439.47* (52)</td>
<td>163.72* (49)</td>
<td>105.85* (45)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSEA</td>
<td>.20</td>
<td>.12</td>
<td>.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NNFI</td>
<td>.72</td>
<td>.91</td>
<td>.95</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CFI</td>
<td>.78</td>
<td>.94</td>
<td>.97</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model Comparison</td>
<td>1 versus 2</td>
<td>2 versus 3</td>
<td>2 versus 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta \chi^2$ (d.f.)</td>
<td>275.75* (3)</td>
<td>57.87* (4)</td>
<td>3.04* (4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept Mean (variance)</td>
<td>1.90* (.15*)</td>
<td>1.76* (-10)</td>
<td>3.04* (.80*)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope Mean (variance)</td>
<td>.68* (.15*)</td>
<td>1.32* (.04)</td>
<td>.74* (.88*)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quadratic Mean (variance)</td>
<td>-26* (.06)</td>
<td>1.32* (.04)</td>
<td>-26* (.06)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Task Conflict</th>
<th>Model 1: No growth</th>
<th>Model 2: Linear</th>
<th>Model 3: Quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2$ (d.f.)</td>
<td>379.66* (52)</td>
<td>93.63* (49)</td>
<td>66.61* (45)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>.20</td>
<td>.08</td>
<td>.06</td>
</tr>
<tr>
<td>NNFI</td>
<td>.81</td>
<td>.97</td>
<td>.99</td>
</tr>
<tr>
<td>CFI</td>
<td>.85</td>
<td>.98</td>
<td>.99</td>
</tr>
<tr>
<td>Model Comparison</td>
<td>1 versus 2</td>
<td>2 versus 3</td>
<td>2 versus 3</td>
</tr>
<tr>
<td>$\Delta \chi^2$ (d.f.)</td>
<td>286.03* (3)</td>
<td>27.02* (4)</td>
<td>27.02* (4)</td>
</tr>
<tr>
<td>Intercept Mean (variance)</td>
<td>3.89* (.94*)</td>
<td>3.89* (1.35*)</td>
<td>3.89* (1.35*)</td>
</tr>
<tr>
<td>Slope Mean (variance)</td>
<td>-.40* (.22*)</td>
<td>-.67* (1.18*)</td>
<td>-.67* (1.18*)</td>
</tr>
<tr>
<td>Quadratic Mean (variance)</td>
<td>.08* (.05*)</td>
<td>.08* (.05*)</td>
<td>.08* (.05*)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Process Conflict</th>
<th>Model 1: No growth</th>
<th>Model 2: Linear</th>
<th>Model 3: Quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2$ (d.f.)</td>
<td>337.61* (52)</td>
<td>181.74* (49)</td>
<td>111.91* (45)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>.18</td>
<td>.14</td>
<td>.09</td>
</tr>
<tr>
<td>NNFI</td>
<td>.82</td>
<td>.90</td>
<td>.95</td>
</tr>
<tr>
<td>CFI</td>
<td>.86</td>
<td>.93</td>
<td>.97</td>
</tr>
<tr>
<td>Model Comparison</td>
<td>1 versus 2</td>
<td>1 versus 2</td>
<td>2 versus 3</td>
</tr>
<tr>
<td>$\Delta \chi^2$ (d.f.)</td>
<td>155.87* (3)</td>
<td>69.83* (4)</td>
<td>69.83* (4)</td>
</tr>
<tr>
<td>Intercept Mean (variance)</td>
<td>3.11* (.94*)</td>
<td>3.04* (.80*)</td>
<td>3.04* (.80*)</td>
</tr>
<tr>
<td>Slope Mean (variance)</td>
<td>.10 (.35*)</td>
<td>.74* (.88*)</td>
<td>.74* (.88*)</td>
</tr>
<tr>
<td>Quadratic Mean (variance)</td>
<td>-19* (.20*)</td>
<td>-19* (.20*)</td>
<td>-19* (.20*)</td>
</tr>
</tbody>
</table>

Note: Unstandardized values shown for intercept, slope, and quadratic means and variances.

* $p \leq .05$

LGM = Latent growth modeling
Beginning with relationship conflict, the nonsignificant variance parameters from the superior-fitting model 3 indicate that there is no significant variability in respondents' initial status for this construct and that respondents increase and decrease at very similar rates. The means values of 1.32 and -0.26 for the slope and quadratic factors, respectively, suggest that once deceleration begins, the rate of increase for relationship conflict is greater than its rate of decrease. Like those for relationship conflict, the parameters for process conflict suggest that it is characterized by significant positive growth in earlier measurement occasions and significant negative growth in latter measurement occasions, with acceleration occurring at a greater rate than deceleration. Unlike for relationship conflict, however, variances for the intercept, slope, and quadratic factors of process conflict are all significant. The latter indicates that there is significant variability in the initial status of individuals on this construct and that there is significant variability in respondents' rates of positive and negative change across time. Although not shown in Table 6.4, the covariances between the initial status factor and the slope and quadratic factors for process conflict are 0.28 (nonsignificant [ns]) and -0.06 (ns), respectively. This indicates that there is not a significant relationship between the level of process conflict reported by respondents at time 1 and the rate at which process conflict increases or decreases at later time periods. For example, respondents reporting high initial levels of process conflict do not necessarily experience increased process conflict at greater rates than those reporting low initial levels, or vice versa. The significant covariance of -0.34 (p = 0.05) between the slope and quadratic factors suggests that respondents exhibiting higher rates of acceleration in process conflict are likely to also exhibit lower rates of deceleration.

Task conflict is the only variable for which LGM results indicate negative growth during the earlier measurement occasions and possible positive growth during the later ones. Significant variances for the intercept, slope, and quadratic factors indicate that there is variability in the initial status of individuals on this construct and that there is significant variability in rates of positive and negative change for task conflict across time. Note that the rate of acceleration, as indicated by the quadratic mean value, is very small (even though it is statistically significant). This very small rate of acceleration is likely one reason why no clear acceleration for task conflict can be seen in Figure 6.1. As with process conflict, the covariances between the initial status factor and the slope (-0.39; ns) and quadratic factors (0.07; ns) for task conflict are not significant, indicating that there is no relationship between the level of task conflict reported by respondents at time 1 and the rate at which it decreases or increases at later time periods. Significant covariance of -0.23 (p = 0.05) between the slope and quadratic factors suggests that respondents exhibiting higher rates of deceleration in task conflict are likely also to exhibit lower rates of acceleration—as might be expected as respondents near completion of the task. Overall, these results suggest that true variability over time does exist for all three types of conflict, and they provide an indication of the nature of intra- and interindividual patterns of variability for each.
Testing for Differences in Patterns of Variability

Results for the multigroup analyses are presented in Table 6.5. Recall that prior to estimating multigroup LGM models, however, LGM models identical to those estimated for the entire sample were analyzed separately for high and low performers. For high performers, the final model obtained for all types of conflict specifies quadratic growth. For low performers, the quadratic model was obtained for relationship conflict and process conflict, but not for task conflict. As is suggested by Figure 6.3, only linear negative growth appears to occur for low performers on task conflict. Because the nature of growth in task conflict is so different for high performers and low performers, it is not appropriate to estimate the multigroup LGM models for this variable. Nonetheless, this difference does confirm substantial variation in patterns of change for task conflict that are associated with high versus low performance.

As is shown in Table 6.5, the second LGM model does not fit significantly differently from the first model for both relationship conflict and process conflict. For all remaining model comparisons, the only significant difference in fit is between models 3 and 4. The fact that model 4 fits significantly worse than model 3 for both relationship and process conflict suggests that the quadratic slopes differ significantly between the high and low performers. Thus, the final LGM model that best represents both relationship conflict and process conflict is one in which intercept and slope means and intercept, slope, and quadratic variances are constrained to be equal across high and low performers. Because they are significantly different, quadratic means should be allowed to freely vary across the two groups in the final models for relationship conflict and process conflict. In other words, for both types of conflict, high and low performers do not significantly differ in their mean initial status or mean rate of increase, nor do they differ significantly in their interindividual variance in initial status, rate of increase, and rate of decrease. High and low performers only significantly differ in their mean rate of decrease. These findings also confirm—albeit more subtly than for task conflict—variation in patterns of change between high and low performers for relationship and process conflict.

To further understand the nature of differences in latent growth between high and low performers, it is necessary to examine the intercept and slope and (where appropriate) quadratic means, variances, and covariances across both groups. These findings are presented in Table 6.6. Note that the parameters presented in Table 6.6 for relationship and process conflict are taken from model 7 of the simultaneous multigroup analyses described previously. The results for task conflict are taken from the separate analyses for high and low performers conducted prior to the multigroup analyses.

As is suggested by Figures 6.2 and 6.3 and Table 6.6, the observed intercept, slope, and quadratic mean and variance parameters for relationship conflict and process conflict follow the same basic patterns of direction and significance for both high and low performers. Nonetheless, model comparison results indicate that the quadratic means are significantly different. The quadratic means shown in Table 6.6
Table 6.5
Multigroup LGM Model Fit and Comparison for High and Low Performers

<table>
<thead>
<tr>
<th>Relationship conflict</th>
<th>$\chi^2$ (d.f.)</th>
<th>RMSEA</th>
<th>NNFI</th>
<th>CFI</th>
<th>Model Comparison</th>
<th>$\Delta\chi^2$ (d.f.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Process conflict</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1: Unconstrained</td>
<td>194.23*</td>
<td>0.07</td>
<td>0.97</td>
<td>0.97</td>
<td>1 versus 2</td>
<td>0.23</td>
</tr>
<tr>
<td>Model 2: Equal intercept means</td>
<td>194.46*</td>
<td>0.07</td>
<td>0.97</td>
<td>0.97</td>
<td>1 versus 2</td>
<td>0.25</td>
</tr>
<tr>
<td>Model 3: Equal slope means</td>
<td>196.21*</td>
<td>0.07</td>
<td>0.97</td>
<td>0.97</td>
<td>2 versus 3</td>
<td>0.25</td>
</tr>
<tr>
<td>Model 4: Equal quadratic means</td>
<td>204.10*</td>
<td>0.07</td>
<td>0.97</td>
<td>0.97</td>
<td>3 versus 4</td>
<td>7.89*</td>
</tr>
<tr>
<td>Model 5: Equal intercept variances</td>
<td>196.23*</td>
<td>0.07</td>
<td>0.97</td>
<td>0.97</td>
<td>3 versus 5</td>
<td>0.02</td>
</tr>
<tr>
<td>Model 6: Equal slope variances</td>
<td>199.73*</td>
<td>0.07</td>
<td>0.97</td>
<td>0.97</td>
<td>5 versus 6</td>
<td>3.50</td>
</tr>
<tr>
<td>Model 7: Equal quadratic variances</td>
<td>200.41*</td>
<td>0.07</td>
<td>0.97</td>
<td>0.97</td>
<td>6 versus 7</td>
<td>0.68</td>
</tr>
</tbody>
</table>

* $p \leq .05$

LGM = Latent growth modeling
Table 6.6
Intercept, Slope, and Quadratic Parameter Estimates and Covariances for High and Low Performers

<table>
<thead>
<tr>
<th>Relationship conflict</th>
<th>Intercept Mean (variance)</th>
<th>Slope Mean (variance)</th>
<th>Quadratic Mean (variance)</th>
<th>Covariances</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Intercept</td>
</tr>
<tr>
<td>High performance</td>
<td>1.77* (-.01)</td>
<td>1.33* (.23)</td>
<td>-.30* (-.04)</td>
<td>Slope</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Quadratic</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.06</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.03</td>
</tr>
<tr>
<td>Low performance</td>
<td>1.77* (-.01)</td>
<td>1.33* (.23)</td>
<td>-.22* (-.04)</td>
<td>Slope</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.44*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Quadratic</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.10*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.02</td>
</tr>
<tr>
<td>Task conflict†</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High performance</td>
<td>3.85* (1.48*)</td>
<td>.84* (1.33*)</td>
<td>.14* (.06*)</td>
<td>Slope</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.50</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Quadratic</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.27*</td>
</tr>
<tr>
<td>Low performance</td>
<td>3.88* (1.00*)</td>
<td>-.44* (.23*)</td>
<td></td>
<td>Slope</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.08</td>
</tr>
<tr>
<td>Process conflict</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High performance</td>
<td>3.16* (.72*)</td>
<td>.69* (.77*)</td>
<td>-.21* (.19*)</td>
<td>Slope</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.17</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Quadratic</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.32*</td>
</tr>
<tr>
<td>Low performance</td>
<td>3.16* (.72*)</td>
<td>.69* (.77*)</td>
<td>-.13* (.19*)</td>
<td>Slope</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.60</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Quadratic</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.18*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.29*</td>
</tr>
</tbody>
</table>

Note: Unstandardized values shown.

* \( p \leq .05 \)

† Values for task conflict are taken from separate analyses of high and low performers rather than from simultaneous multigroup analyses. The latter analyses were precluded by the fact that the quadratic model fit for high performers, whereas the linear model fit for low performers.
Figure 6.2
Change in Latent Means across Time for High Performers Only

Figure 6.3
Change in Latent Means across Time for Low Performers Only
for relationship conflict and process conflict suggest that low performers decelerate in these two types of conflict at a slightly lower rate than their high-performing counterparts. Combining results from the latent growth models and the latent means, we generally can conclude that low performers accelerate to higher levels of relationship conflict and decelerate from those higher levels more slowly than do high performers. Regarding process conflict, low performers and high performers accelerate at similar speeds to similar levels, but low performers appear to exhibit less overall deceleration over time.

The factor covariances in Table 6.6 indicate that the relationships between the intercept factor and both the slope and quadratic factors are significant for low performers on relationship conflict but are not significant among high performers. These results suggest that for low performers, high levels of relationship conflict at time 1 are associated with greater increases in relationship conflict over the earlier measurement periods and with smaller decreases in relationship conflict between times 3 and 4. The lack of significant covariances for relationship conflict among the high performers indicates that their initial levels on this type of conflict are not associated with later rates of increase or decrease and that the rate of increase is not associated with the rate of decrease. High and low performers also show different patterns of covariance for process conflict. In this case, the slope factor and quadratic factor significantly covary for high and low performers, suggesting that, for both, a higher rate of increase on process conflict is associated with lower rates of decrease. This similarity notwithstanding, the process conflict intercept factor significantly covaries with the quadratic factor for low performers only. Thus, for low performers, it seems that higher initial process conflict is associated with lower rates of decrease in process conflict later on.

Task conflict is the one measure for which quadratic growth does not hold for both high performers and low performers. Nonetheless, it is instructive to consider the intercept, slope, and (for high performers) quadratic parameters for this construct as well. Though high performers show a general decrease in task performance across all four measurement periods, the rate of decrease levels off between times 3 and 4 (Figure 6.2), which produces support for the quadratic model. For low performers, however, there is only evidence of linear decrease in task conflict. The significant covariance between the slope and quadratic factors for high performers on task conflict implies that greater rates of decrease on task conflict are associated with lower rates of increase. For low performers, the intercept and slope factors are not significantly associated, suggesting that their initial status on task conflict is not associated with their ultimate rates of deceleration.

Testing for Variation in Within-Group Consensus across Time
ICC(1) and ICC(2) values are presented in Table 6.7. For relationship conflict, consensus increases and decreases through the four measurement points in the performance episode but shows an overall pattern of increase over time. Both types of ICC
values start at a moderate level for relationship conflict, increase at time 2, and then decrease slightly before increasing again at time 4—perhaps suggesting a reassessment of relationship conflict at time 3 in light of the approaching project deadline. Within-group consensus for process conflict is essentially nonexistent at time 1, but it steadily increases substantially, for both ICC(1) and ICC(2), across the remaining three time periods. Finally, groups exhibit very little agreement in rating task conflict at times 1, 2, and 4, but they show low to moderate levels of agreement on task conflict at time 3. Overall, these results suggest that group members may go through differing episodes or periods of agreement and disagreement as the different types of conflict emerge. It is also interesting to note that although the pattern of consensus over time is consistent for both high and low performers, the high performers generally exhibit higher levels of consensus (Table 6.7).

DISCUSSION

Although researchers have suggested that efforts to conceptualize groups as dynamic systems have been problematic (for example, Arrow et al., 2000), in this work we explicitly suggest that advances in our conceptualization of time and temporal characteristics (Zaheer et al., 1999), of collective constructs (Morgeson and Hofmann, 1999), and of groups (Marks et al., 2001; Arrow et al., 2000) give us an opportunity to revisit such a conceptualization. Furthermore, we suggest that this extant research, combined with advances in the empirical tools available to researchers, gives us the means to advance in a structured and incremental manner our understanding of groups as dynamic systems. As one step, we have suggested a way to establish whether a construct can appropriately be described as an emergent state for analytical and conceptual purposes through analyses that reflect concerns with stability of meaning, variability, and variation in patterns of change across groups and concerns about within-group consensus. In our examination of conflict, we have found evidence to suggest that conflict in groups is amenable to conceptualization as an emergent state. In this section, we discuss the implications of our work.

IMPLICATIONS

The work required to pursue a conceptualization of groups as dynamic systems can benefit from an incremental perspective that relies on current cross-sectional work as a starting point. An important implication of our work is that conceptualizing groups as dynamic systems does not require us to abandon current tools and perspectives. In fact, a proper research agenda should rely on cross-sectional studies to provide us with the means to initially characterize relationships between constructs that are of interest, such as task conflict and performance. We suggest that a useful way
Table 6.7
ICC Values at Each Time Period for the Entire Sample, High Performers, and Low Performers

<table>
<thead>
<tr>
<th>Conflict Type</th>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3</th>
<th>Time 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>High</td>
<td>Low</td>
<td>All</td>
</tr>
<tr>
<td>ICC (1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relationship</td>
<td>.10</td>
<td>.21</td>
<td>.03</td>
<td>.25</td>
</tr>
<tr>
<td>Task</td>
<td>-.03</td>
<td>-.06</td>
<td>-.01</td>
<td>-.06</td>
</tr>
<tr>
<td>Process</td>
<td>-.11</td>
<td>-.12</td>
<td>-.10</td>
<td>.05</td>
</tr>
<tr>
<td>ICC (2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relationship</td>
<td>.32</td>
<td>.51</td>
<td>.12</td>
<td>.57</td>
</tr>
<tr>
<td>Task</td>
<td>-.14</td>
<td>-.28</td>
<td>-.05</td>
<td>-.31</td>
</tr>
<tr>
<td>Process</td>
<td>-.70</td>
<td>-.75</td>
<td>-.58</td>
<td>.19</td>
</tr>
</tbody>
</table>

ICC = Intraclass correlation coefficient
to bring together existing cross-sectional research with dynamic explanations of group phenomena is to build a bridge between them. Such a bridge would allow us to see the points of contact between the two perspectives, allowing us to advance both.

For us, the cross-sectional work on conflict conducted in the last decade was a solid starting point in our thinking. In particular, the discrepancies in the literature documented by De Dreu and Weingart (2003) were invaluable in framing the need for the exploration of a dynamic characterization of conflict. Their summary of differences in correlations among conflict constructs and the conflicting findings in the relationship between conflict and performance suggested the need for a more detailed examination. For us, these findings suggested that cross-sectional designs might be introducing some difficulties of their own and that these challenges may be overcome with a dynamic perspective. Our use of extant literature as a starting point highlights the tremendous value of meta-analytic procedures in the study of groups. When summaries of research point to inconclusive or contradictory evidence, we may find questions and contradictions that are amenable to examination using a dynamic perspective.

Cross-sectional work is also important because it allows us to tease out potential relationships between constructs. For example, Simons and Peterson (2000) examined the relationship between task conflict and relationship conflict and found that trust in the group is an important factor that allows members to separate the two. In chapter 8, exploration is continued of the interplay of trust and conflict through the addition of another variable—respect—as influencing the relationship. These findings raise several questions from a dynamic perspective. One important question is whether trust and respect are dynamic elements in the group. For instance, it seems reasonable that trust is dynamic, since interactions among members can affect how they perceive one another's reliability, which influences trust. A second question is how stable trust and respect might be over a particular timescale, whether they share a timescale with conflict, or whether they are more stable or more unstable than conflict. After characterizing the dynamic (or static) properties of trust and respect, further examinations could focus on the dynamic interplay of trust, respect, and conflict.

Our findings also point to some potential avenues to strengthen cross-sectional research design. In particular, our results suggest that it is critical to pay increased attention to the timing in the measurement of dynamic constructs. Timing in measurement matters in two different ways. First, ensuring common timing in data collection across groups in a sample ensures comparability across those groups. Dynamic constructs exhibit different characteristics across a single performance episode. Particularly in a group that exists for a single performance episode, the choice to collect data at the beginning, middle, or end of the performance episode should be carefully deliberated.
In addition to highlighting empirical concerns, our work also points to challenges to consider dynamic elements in groups from a theoretical standpoint. Our work suggests that as we develop causal explanations involving dynamic phenomena in groups, we will need to consider temporal aspects (such as when things happen) more explicitly. For example, chapter 4 focuses on the initial composition of groups and how that influences conflict. In this instance, a critical part of their study design is the passage of time, which allows for the emergence of conflict within the group.

As we move forward in our work, we will also need to account for patterns of emergence in dynamic properties and how they might be related to other emergent elements. For example, in our findings we noted a difference in the rate of change of task conflict between high- and low-performing groups. The differences in the slopes (identifying decreases in task conflict) may be indicative of differences in the development of effective conflict resolution. Groups that develop effective conflict resolution approaches may be in a better position to capitalize on differences of opinion precisely because they are more effective at bridging those differences. To the extent that successful groups are developing idiosyncratic approaches to conflict resolution, this may be a reflection of the emergence of norms around conflict.

Also, to the extent that we use single-point measures to characterize dynamic phenomena, it will be necessary to explain the single-point measure in the context of emergence in the group. As we suggested earlier, it is possible that some of the contradictory evidence currently present in the literature might be due to such problems. In the earlier part of this chapter, we noted that the difficulties in linking task conflict and performance (De Dreu and Weingart, 2003) could be caused by differences in measurement timing. Here, we suggest that these differences in measurement timing might also reflect differences across studies in the dynamic characteristics of conflict (such as their starting characteristics, their duration, and so on).

An important point to highlight is that much of the research on conflict is conducted using groups that have a definite beginning and end to their activities. Previous research has shown that such timing patterns can influence the work of groups (Gersick, 1988, 1989; Okhuysen and Waller, 2002). For temporary groups, some elements are likely to follow their existence or life term strongly, with patterns that closely match the groups' starting and ending points. However, other temporal patterns are also possible. As part of their analysis, Jehn and Mannix (2001, pp. 242 and 243) used “group value consensus” to describe “central values” that are held by members, and they measured the “degree of consensus” on those values. Jehn and Mannix (2001) use these group values and the degree of consensus among members as stable underpinnings on which the student groups interact and on which they rely to express and resolve conflict.

Ongoing groups such as university departments, manufacturing teams, or government agency groups are more likely to possess these longer-term, changeable, but relatively stable, characteristics. These differences in temporal dynamics may require
slightly different approaches for study. For example, longer-term groups are less likely to have task beginnings and endings, and they may be more likely to have group norms (Feldman, 1984) that persist for longer periods of time. Elements such as norms, though, may have temporal dynamics of their own, encapsulated in processes to create, maintain, and enforce them, and may have particular growth and decay dynamics. In addition, longer-term groups may be affected by task performance dynamics of their own. For example, sales groups may be entrained (Ancona and Chong, 1996) in fiscal reporting cycles, driving higher performance toward the end of three-month or one-year intervals, potentially affecting other group elements such as conflict over those cycles.

FROM STATIC AND DYNAMIC TO A FOCUS ON INERTIAL INFLUENCES

One area that deserves greater attention to help us further our understanding of groups as dynamic systems is the difference in rates of change among constructs. As Zaheer et al. (1999) point out, when we consider a phenomenon we must also consider its time scale—that is, the right duration of time to see its evident effects. Thus, at the simplest level we need to characterize elements as having slower or faster rates of change.

As we expand our understanding of groups to include phenomena such as membership change, however, we are likely to find few purely static constructs. Thus, conceptualizations that discuss group elements as subject to different levels of inertial influences might be more helpful than ones that focus on strict differences between static and dynamic properties. In addition, a focus on the relative rate of change of constructs would also be useful to help specify where cross-sectional and longitudinal study designs might be appropriate. In particular, cross-sectional designs are most likely to be informative when the likelihood or potential for change over a unit of time is similar across constructs.

In the same way, though, it may be necessary to focus on the development of measurements for phenomena that are similar in the content they capture but that occur at different time scales. Continuing with the study of conflict, for example, might require developing an understanding of conflict in the very short term, such as when conflict causes emotional displays (like anger or frustration). A medium-term analysis such as the one we have presented here might account for conflict as it affects and is affected by other group processes. Finally, a longer-term perspective, in which constructs such as hostility in groups or psychological safety (Edmondson, 1999) are studied, might give us insight into conflict spirals. The need for this research comes from a desire to understand when, for example, conflict becomes a norm that group members operate under, reflecting a more stable situation than the one we describe here. At such a stable state, conflict may cease to act as an emergent state and may instead become an attractor, a global variable that influences other elements in the group (Arrow et al., 2000).
CROSS-LEVEL ISSUES

Our work raises questions related to the aggregation of members' individual-level interpretations of their interactions to group-level emergent states, particularly on the role of intermember consensus in group research. Recent research has used within-group agreement as a test (and a justification) for the aggregation of individual-level data into groups (Bliese, 2000). Chapter 3 explores some of the difficulties involved in aggregating conflict measures. In particular, chapter 3 usefully explains many of the challenges of measurement when multiple interpretations of conflict exist. However, if we are to characterize some group elements as emergent states, theory must account for the possibility that, at certain times during the emergence process, different individuals may see the situation in their group differently and that their perspectives may not converge at those times. Our results suggest that group members can vary in their levels of consensus across a performance episode. Although our data were unable to fully address this issue, it is possible that similar patterns of consensus repeat over performance episodes, provided that membership and other contextual characteristics remain fairly stable. It is also possible that, for ongoing groups, group members ultimately reach a relatively stable level of consensus about levels of all three types of conflict.

Another area that deserves attention is the role of recalibration of variables over time. Further work is required to understand under what conditions individual-level interpretations (or emergent states at the group level) can undergo a significant, steplike change. For example, consider an individual who possesses a low tolerance for conflict. This individual might initially judge the level of conflict in a group as quite high, although over time the individual can recalibrate for this specific group. Similarly, when a group loses a member, it is possible that informal coordination networks are disrupted and perceptions of what constitutes high or low task conflict and/or process conflict could change. An even more intriguing possibility is raised in chapter 10, which explores how interventions from an external party can modify intrateam conflict dynamics. Such interventions are interesting because of the control they afford to managers and leaders in the recalibration of conflict. Although recalibrations such as these are typically considered problematic from an empirical perspective, we should explore whether they might be re-conceptualized as a "normal" part of the group process consistent with conceptions of emergent states.

Using emergence as an analogy to understand groups also raises a question regarding the predictability of group behavior. In many computer simulations of emergent systems, end states emerge that reflect stability of some form. Three types of stability, for example, include extinction (the death of the system), hyperstability (a state with no movement), and oscillation (in which the system repeatedly shifts
from one arrangement to another in an alternating manner). It is unlikely that individual elements of groups (such as group conflict) will predictably follow one of these patterns of behavior. It may be the case, however, that the group as a whole might follow such a pattern. Behavior that is destructive to groups is relatively common (Hackman, 1990), and hyperstability has been documented in at least some instances (Katz, 1982). In the absence of external influences on a group (in the form of feedback or changes in membership, for example), groups may achieve these stable arrangements. Further exploration on whether an incorporation of these ideas is desirable would be worthwhile.

Naturally, there are also limits to the use of an emergence perspective to explain groups. Perhaps most importantly, emergence typically discusses systems or higher-level entities made up of very simple components with simple interaction rules (Holland, 1998). In addition, the component elements in emergent systems are typically presumed to have simple (or no) intent. Each of these assumptions is difficult to support in the case of individuals interacting in a group situation. However, there are still benefits to considering groups as having emergent elements. In particular, such a conceptualization forces us to more completely characterize the interconnections between individuals and their collective behavior.

A final implication of our work comes from the nature of group processes, in which the aggregation of characteristics of individuals, combined with the interactions between members, gives rise to group-level variables. As with any situation where cross-level influences exist, the examination of groups as dynamic systems is likely to increase in complexity as necessary to account for those cross-level influences. For example, consider an individual with a relatively stable psychological characteristic—for example, a tolerance to conflict. Examining group conflict and tolerance to conflict simultaneously requires accounting for two forms of complexity. On one hand, it is important to account for the interactions between individuals that become group behavior. However, this aggregation must also account for two properties (for example, a personality variable and an emergent state) with different timescales. These types of cross-level and cross-temporal interactions are likely to be some of the most challenging ones.

CONCLUSION

Our examination of conflict is a very modest step in the path to conceptualizing groups as dynamic systems. However, we believe that such a conceptualization is, in fact, the next step in scholars' examinations of groups. These examinations will be made of small steps such as the two we have outlined—that is, the detailed description of emergent states as one example of a dynamic element and the application of this description to conflict in groups.
NOTES

1. For an exception that treats conflict as dependent on timing, see Jehn and Mannix (2001).

2. Of course, performance is only one of many possible variables that might be associated with groups that are experiencing differing levels of conflict. For instance, we might also expect groups experiencing high initial levels of task conflict to exhibit different patterns of relationship conflict from those experiencing low initial levels of task conflict.

REFERENCES


Chan, D. 1998. The conceptualization and analysis of change over time: An integrative approach incorporating longitudinal mean and covariance structures analysis (LMACS) and multiple indicator latent growth modeling (MLGM). *Organizational Research Methods*, 1, 421–483.


APPENDIX 6.A:
DETAILED DESCRIPTION OF ANALYTICAL PROCEDURES

TESTING FOR STABILITY OF MEANING ACROSS TIME

In the unconstrained first model, factor loadings, factor means, and factor variances were all freely estimated. The second model was identical to the first, but identical indicators were constrained to be equal over time. If the chi-square value between these two models did not significantly worsen, then there was evidence of measurement invariance, and, following the logic of parsimony, the second model was retained over the first for further analyses. The third model was identical to the second, but it added the constraint of equal error variances for identical indicators over time. A nonsignificant change in fit between models 2 and 3 would provide additional evidence of measurement invariance, and the better-fitting model would be retained for comparison with the fourth model. Chan (1998) points out, however, that even if factor loadings remain constant across time, "the error variances...associated with identical indicators need not be equal across time. In fact, if reliability of an indicator remains constant across time and there are differences in true variance across time, we would actually expect error variances to differ across time because observed variances would differ across time" (p. 449). The fourth model was identical to the superior-fitting, most parsimonious, previously tested model with the addition of all factor means being constrained to be equal over time. If this model exhibited a nonsignificant change in fit from the previously retained model, then there was evidence that no growth occurred in respondents across time. Alternatively, if model 4 was rejected, then it was reasonable to examine the given construct for latent growth over time in the next phase of analyses, and it was also reasonable to estimate the fifth and final model of the present phase of analyses. The final model was identical to the previously retained, superior-fitting model, but all factor variances were also constrained to be equal across time. Comparing the fifth model to the previously retained model gave an initial indication of the nature of interindividual differences in intraindividual change. As such, assuming the initial model comparisons provided evidence of measurement invariance, models 4 and 5 provided preliminary evidence regarding the second characteristic of an emergent state.

TESTING FOR VARIABILITY OVER TIME

The first model was a no-growth model that specified a single second-order factor (onto which loaded the four first-order factors defining a given construct as measured at each of the four time periods) representing the intercept, or initial status,
of the given conflict construct. Poor fit for the no-growth model indicated that some form of growth model may be appropriate. The second model was identical to the first but specified a linear growth trajectory by adding a second-order slope factor. Factor loadings between the slope factor and the four first-order construct factors were fixed to the values of 0, 1, 2, and 3, respectively, to represent the four equally spaced time periods across which each conflict construct was measured. If the second model fit the data significantly better than the first, there was support for linear growth across time and there was justification for estimating the final latent growth model. The last model was identical to the second, but it also included a second-order quadratic factor. Factor loadings between the quadratic factor and the first-order conflict factors were respectively fixed to the values of 0, 1, 4, and 9 (that is, the slope-factor-loading values squared). If this third model fit the data better than the second, there was evidence of nonlinear change for the given construct.

**Testing for Predictive Ability among High and Low Performers**

The first latent growth modeling multigroup model that was estimated was, again, an unconstrained model. That is, none of the parameters associated with the second-order intercept, slope, and quadratic factors were constrained to be equal between the two groups. However, on the basis of results from the single-group analyses, factor loadings for identical indicators were constrained to be equal across time in all models. Further, on the basis of results from the first set of multigroup analyses (see Results), factor loadings, error variances, and factor variances were constrained to be equal across the two groups in all models. Acceptable fit for the unconstrained model would offer further confirmation that the same shape of growth was applicable to both groups. The second model was identical to the first but constrained the intercept factor means to be equal across the two groups. If model 2 did not fit significantly worse than model 1, there was evidence that the initial status for both groups was similar, and model 2 was retained for the next comparison. Model 3 was identical to model 2 but added the constraint of equal slope factor means across the two groups. If the difference in fit between models 2 and 3 was not significantly different, there was evidence of no significant difference in slopes between groups, and model 3 was retained for the next comparison. This pattern of model comparison continued for the remaining four models. Thus, model 4 was identical to the previously best-fitting model, but the quadratic means were constrained to be equal across groups. Models 5–7 successively added the additional constraints of equal intercept, slope, and quadratic variances to the previously estimated superior-fitting models.