Explaining Change: Theorizing and Testing Dynamic Mediated Longitudinal Relationships

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Many disciplines of scholarship have developed theories that involve dynamic mediated (and multilevel) relationships among constructs. However, most research does not hypothesize or test these dynamic relationships in a manner consistent with theory. In this article, the authors address this disconnect by first noting the theoretical and methodological limitations of ignoring dynamic mediated (and multilevel) relationships. Specifically, the authors show that theory testing suffers and statistical conclusions are often erroneous when dynamic mediation is ignored. The authors then present several ways of conceptualizing dynamic mediated relationships and then turn to summarizing two statistical models for analyzing such data. They conclude with a brief example from a team performance context.

Keywords: *multilevel modeling; mediation; change over time; time-varying predictors; dynamic relationships*

Theory building in the organizational sciences has moved from the examination of static, bivariate relationships to longitudinal, multivariate relationships. This is a welcomed change because organizational and psychological processes are not static but instead develop, change, and evolve over time. Consequently, most theories are inherently concerned with

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explaining relationships between variables over time, even if the issue of time is not explicit within the theory (George & Jones, 2000). Such theories are prominent within the micro- (e.g., ability-motivation-performance; Kanfer & Ackerman, 1989; stage theories of trust; Lewicki & Bunker, 1995, 1996; Rousseau, Sitkin, Burt, & Camerer, 1998) and macroliteratures (e.g., strategic fit; Zajac, Kraatz, & Bresser, 2000; relationships between human resource [HR] practices and firm performance; Schneider, Hanges, Smith, & Salvaggio, 2003).

These are dramatic improvements, but there remain important discrepancies between current management theories versus the hypotheses, methods, and analyses used to test those theories. In this article, we argue that although many theories articulate dynamic mediated (and frequently multilevel) relationships, most empirical research has failed to hypothesize, design, and test for such relationships in the manner prescribed by theory. A *dynamic relationship* is defined as a longitudinal relationship between two variables. Notably, *both* variables are measured repeatedly in dynamic relationships. *Dynamic mediated relationships* represent instances where the mediator and dependent variables, and frequently the independent variable, are measured repeatedly and have a specific hypothesized causal sequence (later we will describe different configurations of dynamic mediated relationships).

This article argues that management scholars must begin to hypothesize and test dynamic mediation. First, we will show that many dominant theories specify dynamic mediated relationships, yet empirical research has ignored this aspect of the theories. Second, we will discuss how ignoring dynamic mediation has severe conceptual and methodological consequences. Conceptually, it leads to proposing "weak" hypotheses that are difficult to falsify and may lead to overestimates of the amount of support for a theory. Methodologically, we review research revealing that cross-sectional designs can lead to severely biased parameter estimates and inaccurate significance tests. We then introduce ways to conceptualize dynamic mediation, as well as a brief summary and empirical demonstration of statistical methods best suited for modeling dynamic mediation. Included in this discussion is the treatment of multilevel dynamic mediation models as a special case of dynamic mediation. Thus, our study extends and integrates the theoretical literature on time and mediation (e.g., George & Jones, 2000; Mitchell & James, 2001) with the methodological literature on longitudinal and multilevel mediation (e.g., Krull & MacKinnon, 1999; Maxwell & Cole, 2007). We believe that addressing these issues will contribute to better hypothesis generation, methodological design, and empirical testing of theory. Perhaps more important, we argue that hypothesizing and modeling dynamic mediated relationships will contribute to a more theoretically rigorous explanation of change processes than is true of current practice.

Dynamic Theories Made Static: Three Illustrative Examples

To illustrate that most theories and models are stated in dynamic terms but hypotheses are stated and tested using static methods, we briefly present illustrative examples from micro- (individual level), meso- (groups and team), and macro- (firm level) domains of scholarship. We also consider both theories and models to illustrate that both are frequently specified in dynamic terms but not tested in the appropriate manner.

Micro- (Individual) Level

Many microtheories hypothesize relationships among constructs that are longitudinal and dynamic, but research has yet to give the attention that the temporal component of these theories should have. Stage theories are a representative example because they clearly specify dynamic relationships but are rarely tested in such a manner. For example, trust development theories (Lewicki & Bunker, 1995, 1996) map the development of trust in an interpersonal relationship to different stages of development of that relationship. In the early stages of a relationship, trust emerges as a result of repeated transactions among the parties involved. This type of trust, called calculus-based trust (CBT), is attributed to the expected benefits of maintaining a relationship surpassing the costs of severing it. As relationships evolve, the parties gain more knowledge about and understanding of each other through repeated interaction and communication. As a result, the parties' actions become more predictable, and knowledge-based trust (KBT) develops in this stage. Finally, as a relationship becomes characterized by an internalization of the parties' desires and preferences, trust becomes identification-based trust (IBT). IBT emerges when the parties have shared goals and values, and as a result, they may act on behalf of each other. According to Lewicki and Bunker (1995, 1996), trust changes from CBT to KBT when the focus shifts from differences to similarities between parties. The transition from KBT to IBT is made when the parties shift from learning about each other to developing a common identity. In summary, stage theories of trust development propose that trust develops and evolves over time and that it has different determinants and mediators that also evolve and change over time.

In a recent review of the trust literature, Lewicki, Tomlinson, and Gillespie (2006) note that the majority of trust research is static and, thus, does not provide details about the dynamics of the evolution of trust over time. Indeed, an examination of the research citing the original work that describes the stage model of trust development (Lewicki & Bunker, 1995, 1996; Shapiro et al., 1992) reveals more than 50 articles, most of which take a static view of trust, regardless of whether they employ single-wave or multiple-wave longitudinal studies. For example, Ross and Wieland (1996) examined the effects of trust and time pressure on mediation strategy in a computer-mediated simulation. They found that high trust between negotiators increased mediators' perceived common ground, leading to inaction, but tested these relationships using static techniques.

Overall, the extant research on trust is limited to static or snapshot investigations of the construct. Consequently, there is little empirical evidence for the dynamics of trust over time. Lewicki et al. (2006) attributed this shortcoming mainly to methodological issues and called for more longitudinal and qualitative studies of trust.

Meso- (Group) Level

We now consider an example from the team performance literature. We pick a team performance example because a longitudinal perspective is present in most theories of team performance (Kozlowski & Bell, 2003) and team performance theories are based on input-process-output models (Hackman, 1987). To illustrate, we examine the temporally based model of team processes proposed by Marks, Mathieu, and Zaccaro (2001). This model proposes that teams engage in task performance in a recurring sequence of action and transition phases, during which different team processes become more or less salient. Transition phases are positioned at the beginning and the end of each cycle and "are periods of time when teams focus primarily on evaluation and/or planning activities to guide their accomplishment of a team goal or objective" (p. 360). Action phases are "periods of time when teams are engaged in acts that contribute directly to goal accomplishment" (p. 360). For example, planning and strategizing are central processes during the transition phases, whereas goal monitoring and coordination are central processes during the action phases. Time is clearly an important component of the proposed model because teams move through different phases. Specifically, the action and transition phases described in the model occur with varying frequency and duration, depending on team inputs and the characteristics of the task. However, it is important to keep in mind that time in this model is just a backdrop for the constant interplay of different team processes that unfold in each performance phase and affect overall team effectiveness. As such, changes in mediating team processes, and not merely the passage of time, explain changes in team performance.

Despite the major role that dynamic relationships and time play in this model, 86 of the 87 articles citing this model (at the time of this writing) are static. Of the nine studies that employed a longitudinal design, only one study examined a dynamic relationship as we have defined it (Mohammed & Angell, 2004), whereas the others employed analyses based on static models. To illustrate further, Tasa, Taggar, and Seijts (2007) explored the development of collective efficacy in teams over time. Although they employed a longitudinal design, the hypotheses and analyses do not venture past the static research framework. For example, Hypothesis 2 states that "at the team level, aggregated teamwork behavior is positively related to subsequent collective efficacy" (p. 20). Notice that in this hypothesis there is no statement about time or duration—it is at best assumed. It is not surprising that given the static framing of the hypotheses, the subsequent data analyses are conducted to test static relationships between variables, despite the longitudinal design adopted by the authors. Finally, Langfred (2007) proposed a model of the effects of conflict on trust, autonomy, and task interdependence, anchored in Marks et al.'s (2001) framework. Langfred argued that his model represents "an ongoing dynamic process that likely is nested within a larger recursive context or more complex arrangement of episodes" (p. 895). However, in spite of this assertion regarding the dynamic nature of the proposed model, as in the previous example, the hypotheses tested in the study do not address dynamic relationships between the variables included in the model.

Macro- (Firm) Level

Our final example differs from the prior two in that it is a model rather than a theory. Specifically, we consider the scholarship within the field of strategic human resource management (SHRM). SHRM scholarship is not characterized by a single theory but really is a broad model or framework specifying that HR practices contribute to changes in the affect, behavior, and cognition of individuals, which in turn relate to performance at individual and firm levels (Becker & Huselid, 2006; Bowen & Ostroff, 2004; Ployhart, 2006). Thus, complementary HR practices such as recruiting, staffing, compensation, and development are expected to enhance the quality of human capital and ultimately firm performance.

However, despite a growing number of studies (see Combs, Liu, Hall, & Ketchen, 2006), most of this research has (a) ignored temporal issues; (b) ignored the mediating processes of employee affect, behavior, and cognition; and (c) ignored the multilevel nature of the model (Becker & Huselid, 2006; Bowen & Ostroff, 2004; Ployhart, 2006; Wright, Dunford, & Snell, 2001). First, time, duration, and dynamics are rarely considered within SHRM models. Theoretically, it is expected that HR practices lead to change in employee affect, cognition, and behavior over time, and in turn, these employee characteristics lead to change in firm performance over time (Bowen & Ostroff, 2004). Most research ignores these temporal dynamics (Wright & Haggerty, 2005). Even when research tries to consider time, such as ensuring that job attitudes precede assessments of firm effectiveness, it often does not consider a dynamic relationship because the variables are not measured repeatedly. Second, mediating processes are rarely considered. The vast majority of research examines a static relationship between HR practices and unit performance and ignores employee affect, behavior, and cognition (Gerhart, 2005). This neglect of mediating processes has resulted in what is called “the black box” of SHRM scholarship and continues to plague the field and limit its theoretical rigor (Becker & Huselid, 2006; Wright & Haggerty, 2005). Finally, even though HR practices exist at the firm or unit level and employee attitudes, behavior, and cognition are formed at the individual level (e.g., Bowen & Ostroff, 2004; Gerhart, 2005), most studies do not adopt a multilevel perspective. To be fair, most studies adequately address issues of aggregation, but for studies where the dependent variable is at the individual level, relatively few consider multilevel mediated relationships.

Issues With Ignoring Dynamic Mediated Relationships

The studies presented above are only a fraction of the empirical studies that suffer from these issues but are representative of the tendency to ask and test static research questions and to generally overlook the dynamic nature of relationships between constructs. Furthermore, although the theoretical frameworks described above are, by far, not the only ones that either directly describe or simply imply dynamic relationships between constructs, they are representative of the lack of empirical research that studies such relationships. It is far from us to dismiss or denigrate existing research or these authors. Rather, we use these studies to illustrate that, despite the obvious competence of scholars, the research was neither conceptualized nor conducted in a manner that fully tests the theory as described. We believe that a possible reason for this apparent neglect is the lack of clear guidelines for conceptualizing, hypothesizing, designing methods, modeling, and testing dynamic relationships. Before discussing dynamic mediated models, we first discuss theoretical and methodological limitations of ignoring dynamic mediated relationships.

Theoretical Issues

We illustrated above how researchers will often specify hypotheses that are stated in static terms even though the theory is stated in dynamic terms. The dangers with such practices are that (a) hypotheses become disconnected from the nature of the relationships specified by the theory, which in turn contributes to (b) failing to test hypotheses based on the theory and (c) ultimately making inferences about the theory that are unwarranted. Static hypotheses are usually proposed that, because of their simplicity, are (d) difficult to falsify and (e) lead to overestimates of support for a theory. Such “weak” hypotheses are the norm in current scholarship (e.g., Mitchell & James, 2001). However, when the theory incorporates dynamic relationships, it is possible to develop “strong” hypotheses that specify time, duration, and the shape of the relationship over time.

Time denotes when an event occurs or when a dynamic relationship is likely to exist. For example, a study examining firm performance before and after a market event (e.g., bank failures) may specify the precise occasion where the relationship changes direction or magnitude. Not all hypotheses will necessarily address issues of a specific time point. For studies that do not have an event or occurrence of interest but merely want to examine how relationships unfold over time, hypotheses can be written to simply emphasize the passage of time (e.g., “X and Y are related over time”).

Duration specifies how long a dynamic relationship should exist. Mitchell and James (2001) argue persuasively why hypotheses should emphasize the duration of relationships. Most dynamic relationships are unlikely to be of the same magnitude over time. For example, even though crystallized intelligence is a strong predictor of individual performance, declines in crystallized intelligence brought about through aging result in it having a weakening relationship with performance over time (Kanfer & Ackerman, 2004). In fact, we suspect it would be quite remarkable for two variables to have an identically strong relationship over time.

Shape refers to the functional form of the relationship over time, such as linear or curvilinear (e.g., negatively accelerated or positively accelerated curve). Nearly all theory and hypotheses in the organizational literature are stated in linear terms. Indeed, in their review of time and theory, Mitchell and James (2001), by their own admission, chose to focus on linear relationships because as they noted, nonlinear relationships “are, as yet, not well represented in the published literature” (p. 532; their review of all articles published in *Academy of Management Journal* in 1999 did not identify a single instance of a nonlinear hypothesis or statistical test). However, one of the hallmarks of an advanced science is the identification and theoretical precision regarding nonlinear relationships over time (George & Jones, 2000). Perfectly linear relationships are rare in the physical world, and they are rare in the psychological world for those subdisciplines that have generated more sophisticated theories. For example, cognitive psychologists have spent enormous energy testing different, precise mathematical functions to represent a learning (or forgetting) curve. Oftentimes, in the organizational sciences, there is little theory to guide the researcher to make a prediction about a specific functional form. It is for this reason that even when the data are longitudinal, researchers will often simply note that “X and Y are related over time.” Note that support for this hypothesis is found if the relationship is linear, quadratic, cubic, or some other type of trend. Simply noting that two variables change together is almost certain to be supported, but how can the support be the same if one curve is linear and another is curvilinear?

Thus, time, duration, and shape are necessary to precisely describe a dynamic relationship. Unfortunately, most hypotheses are proposed in static terms such as “X is related to Y.” For

Table 1
Continuum of Strong to Weak Hypotheses[a]

	Time	Duration	Shape	Hypothesis
Strong	X	X	X	"Change in motivation is related to change in performance, such that the positive (but nonlinear) relationship weakens over time."
↑	X	X		"Change in motivation is positively related to change in performance over time."
↓	X			"Motivation is positively related to performance over time."
Weak				"Motivation is positively related to performance."

[a]To illustrate, suppose a theory proposes that motivation and performance have a dynamic relationship over time such that increases in motivation lead positively to increases in performance. The table presents various ways of specifying this relationship, ranging from strong to weak.

example, suppose a theory proposes that changes in motivation contribute positively to performance change over time. It would be common for this hypothesis to be worded such that "motivation is positively related to performance." Taken literally, the prediction is that motivation will always be positively related to performance indefinitely and linearly. We realize few researchers would make such an extreme claim, but where is this caveat noted within the hypothesis? If we consider this hypothesis in light of time, duration, and shape, we see this hypothesis is rather "weak" and uninformative. Consider now a different wording, such as "change in motivation is related to change in performance, such that the positive relationship weakens over time." This wording makes clear when the relationship is likely to exist, for what duration, and the shape. Table 1 illustrates how time, duration, and shape contribute to the more precise specification of dynamic relationships.

Clearly not every theory or hypothesis must (or can) specify time, duration, and shape. However, the more scholars incorporate these considerations into hypothesis development, the more precise the hypotheses will become. This in turn allows the hypotheses to offer more rigorous and informative tests of theory because they are more falsifiable (Mitchell & James, 2001). This kind of thinking would also stimulate greater refinement in our existing theories. For example, some resource-based scholars have argued that resources are dynamic over time, such that the relationship between a resource and sustained competitive advantage decreases (given constant inputs) (e.g., Helfat & Peteraf, 2003). Although this is a step in the right direction, the next evolution of this theory would require specification of the events (timing) that might weaken the effect of a resource, the "shelf-life" of a resource (duration), and the shape of the relationship between change in resources and sustained competitive advantage (shape).

Methodological Issues

There are also a variety of methodological limitations that result from not using longitudinal dynamic mediated models when such models are appropriate for the theory and data. Many scholars have noted that even when longitudinal designs are employed, they are usually reduced to the analysis of static relationships, thereby eliminating information with considerable value for the theory (Maxwell & Cole, 2007; Mitchell & James, 2001). This is an important limitation because as Maxwell and Cole (2007) note, “by its very definition, mediation implies change over time” (p. 24). There are several methodological issues that occur when mediated data are not modeled longitudinally.

The first set of issues is that parameter estimates become biased when modeling mediation in cross-sectional contexts. Maxwell and Cole (2007) provide a comprehensive treatment of this issue and illustrate that when ignoring or collapsing over longitudinal data to test for mediation, the model becomes misspecified. This misspecification then results in biased parameter estimates. The amount of bias is incredibly severe, to the point where even the sign of the regression weights can change direction! Bias in the parameter estimates also contributes to inaccurate significance tests. This obviously affects the kinds of substantive conclusions that will be drawn from the analysis. As they note, “the substantial bias that typically exists in cross-sectional analyses of mediation can render p values or confidence intervals obtained from cross-sectional data essentially meaningless” (p. 40). These are quite serious and potentially alarming consequences because as their review noted, the vast majority of empirical studies on mediation employ cross-sectional designs.

The second set of issues concerns the ability of the traditional growth model to adequately model dynamic mediation and hence explain change in the dependent variable. In growth models, change in the dependent variable is explained through the use of some coding of time as the independent (or predictor) variable.[1] In this traditional growth model, regardless of whether it is employed through structural equation modeling (SEM) or random coefficient modeling (RCM; sometimes also known as hierarchical linear modeling), time is operationalized as a sensible metric that measures the passing of time (e.g., age, hours, months of experience, number of trials). For example, a simple random coefficient growth model is shown in equations (1) through (3).

$$\text{Level 1: } Y_{ti} = \pi_{0i} + \pi_{1i}T_{ti}\,\pi + e_{ti} \tag{1}$$

$$\text{Level 2: } \pi_{0i} = \gamma_{00} + \gamma_{01}X_i + r_{0i} \tag{2}$$

$$\pi_{1i} = \gamma_{10} + \gamma_{11}X_i + r_{1i} \tag{3}$$

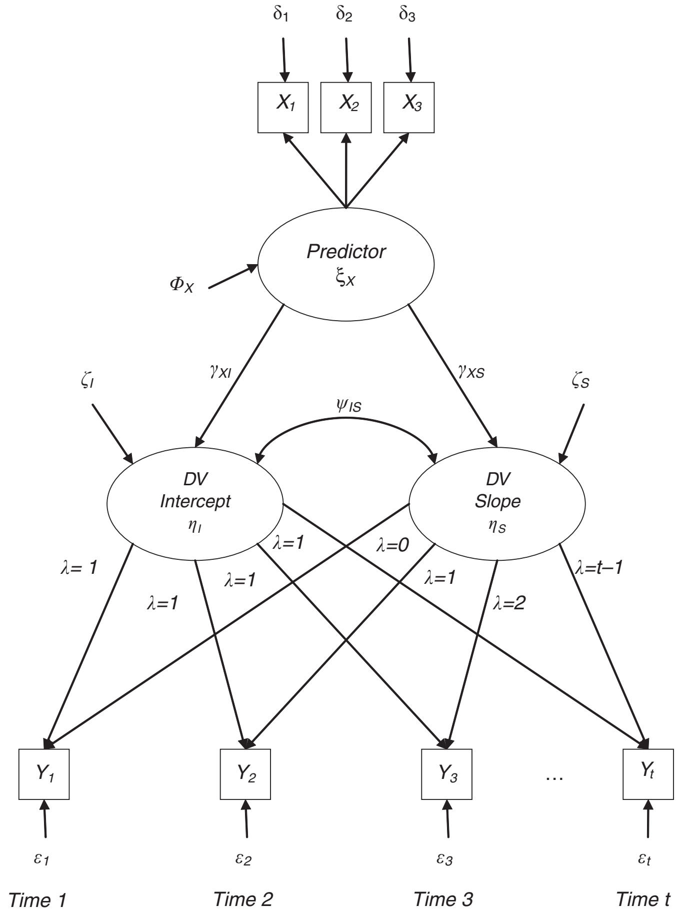
Equation (1) is known as the Level 1 model and contains the repeated (within-subject or intra-individual) effects, and equations (2) and (3) are known as the Level 2 model and contain the (between-subject or interindividual) effects. In Level 1, Y_{ti} is the individual i’s outcome score at time t, T_{ti} is the measure of time (or trend) for individual i, π_{0i} is the outcome at time zero (or initial status), π_{1i} is the average slope for individual i, and e_{ti} is the Level 1 error. The parameters for the Level 2 model are such that γ_{00} is the mean intercept (initial status) for all individuals i, γ_{01} is the mean difference in the Level 1 intercept for a change by one unit in the Level 2 effect (X_i), γ_{10} is the mean slope for all individuals, and γ_{11} is the mean difference in the Level 1 slope for a change by one unit in the Level 2 effect (X_i).

Because these parameters are the same for all Level 1 observations nested within a Level 2 unit, they are referred to as “fixed effects.” The residuals at Level 2, r_{0i} and r_{1i}, represent random effects of unit i on the mean or initial status (π_{0i}) and on the slope (π_{1i}), respectively. The residuals at Level 1 (e_{ti}) are also considered random effects. These residuals are called “random effects” because they fluctuate across individuals or units. A potential explanation for this variation can be provided by between-person (or unit) variables. Thus, for example, intra-individual differences in performance over time (Y) are explained by interindividual differences in self-set goals (X). This is perhaps the most common application of the growth modeling framework in organizational research (Hofmann, Griffin, & Gavin, 2000).

SEM represents another approach for testing growth models; the basic growth model has an identical interpretation to that noted above and is shown graphically in Figure 1 (note that only for the basic growth model are both SEM and RCM approaches identical). For illustrative purposes, we will use formulae when discussing RCM and figures when discussing SEM. We do this because SEM has the nice benefit that graphical representations map directly onto formulaic representations, thus presenting both the SEM figures and formulae is redundant. Specifically, boxes represent manifest variables and circles represent latent constructs. One-headed arrows represent causal relationships (or variances), whereas two-headed arrows represent covariances. Figure 1 illustrates that change in the dependent variable is modeled in terms of latent intercept (subscript “I”) and slope (subscript “S”) parameters as described above. A predictor (X) of change in the dependent variable is also included, as shown by the paths between X and the dependent variable’s intercept (γ_{XI}) and slope (γ_{XS}) factors. In Figure 1, notice that we have allowed the factor loadings to be fixed to represent perfectly linear change. With three or more repeated observations, however, one could allow all of the slope factor loadings to be free except for the first two (coded 0 and 1, respectively) to allow for other forms of change. Chan (1998) provides an excellent overview of these models.

Regardless of whether one uses RCM or SEM, it is important to recognize that this commonly applied growth model does not model a dynamic relationship, much less a dynamic mediated relationship. First, only the dependent variable is measured repeatedly. Second, all predictors of change in the dependent variable are static. Third, there are no mediators that are measured longitudinally. Hence, the dominant application of growth models does not test dynamic mediated relationships. This is perhaps more obvious when viewed from a different perspective. In most theories, time is rarely specified as the cause of change in constructs. For example, performance does not increase or decrease because of time but because of changes in motivation that occur over time. Indeed, we could not identify a single theory within the management sciences that specifies time as the cause of change in some outcome (to be clear, some theories specify that changes will occur over time, but they do not specify time as the cause). Thus, modeling time as an independent variable does not explain why change occurs. Time is simply a metric that allows one to assign numbers to represent change on the dependent variable (Rogosa, 1995). Thus, when the theory specifies dynamic relationships or dynamic mediated relationships between variables, scholars must be aware that the commonly used growth model (equations (1)

Figure 1
A Latent Growth Model With Time-Invariant Predictor
(Indicators for the Predictor (*X*) Are Measured Only Once at Time 1)



through (3) or Figure 1) employing only time as the independent variable does not model this relationship. Time is a convenient metric for describing change, but it is not the explanation for why change occurs.

To summarize, there are a variety of theoretical and methodological issues that result from ignoring dynamic mediation when such models are appropriate for the theory and data. In the next section we describe how to conceptualize dynamic relationships to more directly test dynamic mediated theories.

Configurations for Dynamic Mediated Relationships

Mitchell and James (2001) identified eight different configurations of relationships that vary depending on the nature of change in the independent and dependent variables. Of these types, they only considered one that incorporated mediating variables (Configuration 7). Likewise, they only considered one that addressed moderators (Configuration 8) but not cross-level moderators. Given the increase in multilevel research (e.g., Hitt, Beamish, Jackson, & Mathieu, 2008) and the active research on groups and teams, there should be more scholarship devoted to understanding mediation that is not only dynamic but also multilevel. Similar to the problems with ignoring time in mediation, it has been long known there are serious conceptual (Kozlowski & Klein, 2000; Rousseau, 1985) and methodological (reviewed by Raudenbush & Bryk, 2002) issues with ignoring multilevel data when they exist (e.g., inflated Type I error, biased significance tests, erroneous conclusions). The review by Mitchell and James (2001) was necessarily broad and did not address many critical conceptual and methodological issues with modeling dynamic mediation over time. We extend their broad review by identifying key variations of configurations for dynamic mediation, including a discussion of several conceptual issues unique to dynamic mediation.[2]

The first configuration is simply called "dynamic mediation" because all variables exist at the same level, and the independent (X) and mediator (M) variables are measured repeatedly over time (note that in all models the dependent variable [Y] must be measured repeatedly). This configuration may be illustrated as $X_{(d)} \rightarrow M_{(d)} \rightarrow Y_{(d)}$; we use the subscripts "d" and "s" to denote dynamic and static measurements, respectively. For example, changes in individual goals contribute to changes in motivation, which in turn contribute to changes in performance. This is the type of configuration presented in Mitchell and James (2001). However, there is an important variation of this configuration that may also be relevant. In many theories, the independent variable (X) is a static variable because it is expected to be stable over time, and hence, repeated measurements are not sensible. Therefore, the second configuration may be represented as $X_{(s)} \rightarrow M_{(d)} \rightarrow Y_{(d)}$. For example, personality is enduring throughout most of adulthood, so it would make little sense to measure it repeatedly. As another example, goals may be assessed only once at the start of a performance period, but motivation and performance are assessed repeatedly. The final configuration is called multilevel dynamic mediation because the X and/or M variables exist at higher levels of analysis than the Y variable. Perhaps the most common situation is where X is a static higher level variable, but M and Y are dynamic lower level variables. For example, assuming no turnover, team demographic diversity is a constant, and so team diversity assessed at Time 1 leads to changes in individual motivation over time, which in turn lead to changes in performance over time. We shall illustrate this example later in the article, but please note there are other multilevel configurations available representing various combinations of levels of the variables and static/dynamic representations of those variables.

Modeling Dynamic Mediated Relationships

There are two broad approaches most suitable for modeling dynamic mediated relationships: RCM and SEM. Both have been extensively discussed from a growth modeling framework. However, we reiterate that for most phenomena, time is merely a backdrop or metric for scaling change in the dependent variable; the hypothesized cause of change is not time but change in some other construct or constructs. Thus, the common application of growth models does not provide an adequate basis for modeling and testing dynamic mediation. Fortunately, it is possible to extend the classic growth model to model dynamic mediation by incorporating time-varying predictors. Time-varying predictors are independent variables and/or mediators that change, either naturally or by design, from one measurement occasion to the next (Singer & Willett, 2003). Incorporating time-varying predictors requires additional thought about the underlying nature of the variables and relationships. Of most importance is how one considers the dynamic nature of the independent (X) and mediating (M) variables, because careful specification of the time-varying X and/or M is critical for obtaining appropriate conclusions.

The basic dynamic random coefficient model with a time-varying (dynamic) predictor and time-varying (dynamic) mediator is modeled as follows:

$$\text{Level 1: } Y_{ti} = \pi_{0i} + \pi_{1i}T_{ti} + \pi_{2i}M_{ti} + \pi_{3i}X_{ti} + e_{ti} \tag{4}$$

$$\text{Level 2: } \pi_{0i} = \gamma_{00} + r_{0i} \tag{5}$$

$$\pi_{1i} = \gamma_{10} + r_{1i} \tag{6}$$

$$\pi_{2i} = \gamma_{20} + r_{2i} \tag{7}$$

$$\pi_{3i} = \gamma_{30} + r_{3i} \tag{8}$$

where Level 1 represents intra-individual change and Level 2 represents the interindividual differences in intra-individual change, Y_{ti} is the individual i's outcome score at time t, T_{ti} is the time metric for individual i at time t, M_{ti} is the dynamic mediator (or time-varying mediator) for individual i at time t, and X_{ti} is the dynamic independent variable (or time-varying predictor) for individual i at time t. The estimated parameters in the Level 1 equation (equation (4)) are π_{0i}, which is the outcome when all Level 1 predictors (time and time-varying predictor) are zero; π_{1i}, which is the change in the outcome because of time; π_{2i}, which represents the change because of the dynamic mediator; π_{3i}, which represents the change because of the dynamic predictor; and e_{ti} is the Level 1 residual. In the Level 2 equations (equations (5) through (8)), γ_{00} is the mean intercept (initial status) for all individuals i, γ_{10} is the mean slope for all individuals i, γ_{20} is the mean slope for the dynamic mediator for all individuals i, γ_{30} is the mean slope for the dynamic predictor for all individuals i, and r_{0i}, r_{1i}, r_{2i}, and r_{3i} are the respective Level 2 residuals. Thus, this model includes a time metric, a dynamic predictor, and a dynamic mediator to explain the change. Note that in this model, random effects include e_{ti}, r_{0i}, r_{1i}, r_{2i}, and r_{3i}.

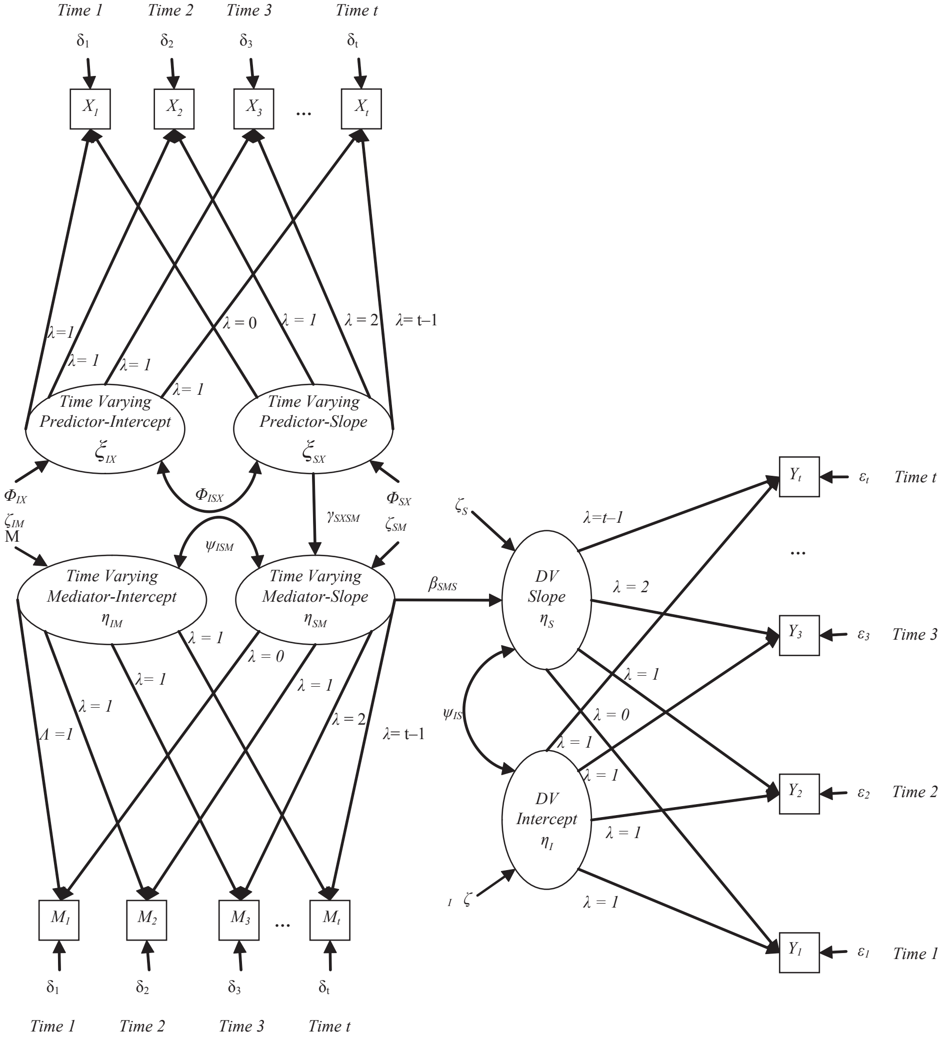
To test for mediation in this model, one should begin by establishing that there is change over time in each of the variables (i.e., there are significant slope parameters). Because the predictor and mediator are at the same level, one may then follow the basic mediation model testing sequence used in ordinary least squares models (see Kenny et al., 2003). First, establish that change in X is significantly related to change in Y by interpreting the slope of X (π_{2i}) in the Level 1 equation $Y_{ti} = \pi_{0i} + \pi_{1i}T_{ti} + \pi_{2i}X_{ti} + e_{ti}$ (the Level 2 equations would be similar to those shown above). Second, establish that change in X is significantly related to change in M by interpreting the slope of X (π_{2i}) in the Level 1 equation $M_{ti} = \pi_{0i} + \pi_{1i}T_{ti} + \pi_{2i}X_{ti} + e_{ti}$ (the Level 2 equations would again be similar to those shown above). Third, include change in M (π_{2i}) and X (π_{3i}) in the same model (equation (4) above) and determine whether the longitudinal relationship between Y and X (π_{3i}) decreases after including the time-varying mediator. If π_{3i} is weaker but still statistically significant, it is evidence for partial mediation; if π_{3i} is no longer statistically significant, it is evidence for full mediation (the Sobel test can also be used to test the mediation effect). Note that if one believes the strength of the relationship of Y with M and X varies over time, one could further test whether M and X interact with the time variable (this begins to fall into questions of moderated mediation and mediated moderation) or test polynomials expressing nonlinear relationships between Y with M or X over time (e.g., including X and X^2 or M and M^2 terms in the model). Finally, as we discuss in more detail shortly, the inclusion of the time variable is not always necessary. We include it here for illustrative purposes but return to this point to indicate when the time variable should and should not be included.

An alternative way to represent dynamic mediation would be to implement cross-domain growth models (see McArdle & Hamagami, 1996) in SEM. Notice in Figure 2 that three growth models are developed: one for change in X, one for change in M, and one for change in Y. Then, change in the X is linked to change in M, which is in turn linked to change in Y. To test for mediation in this model, one can compare a model where X has a direct relationship to Y to a model where X is only indirectly related to Y through M (note that emphasis would be on the slope factors and not the intercepts, given that they model change over time in the constructs). If full mediation is supported, the fit will be significantly better for the model with the additional direct path between X and Y.

Although Figure 2 may appear daunting, it is in fact simply three growth models linked together. Although such a model is more complex than the "typical" growth model, it should be remembered that such a model also has greater degrees of freedom and hence allows for model comparisons and ultimately more falsifiable hypotheses (James, Mulaik, & Brett, 2006). And although there are many more paths that can be estimated (e.g., between intercepts, between intercepts and slopes), such complexity allows for very comprehensive and refined tests of theory (particularly if only those paths specified by the theory are included). Likewise, one can include different lags for X, M, and Y to provide very rigorous tests of mediation over time.

Regardless of whether they are modeled using RCM or SEM, dynamic mediation models represent an important alternative to the traditional growth model because change in M accounts for the dynamic relationship between X and Y. Unlike the cross-sectional context, the dynamic mediation model has two unique features. First, the model evaluates a mediator in a

Figure 2
Diagram of a Dynamic Mediated Longitudinal Model



dynamic longitudinal context. Second, there is variability around this mediated relationship such that the extent of the mediation differs for each person. Therefore, this model evaluates a fundamentally different set of questions than the typical cross-sectional mediated model or even a growth model. One can test whether the mediational paths are stable over time or are subject to change, thus addressing the issue of the dynamics of the mediated relationship over time—precisely as hypothesized in numerous theories (e.g., Austin & Vancouver, 1996; Latham & Locke, 1991; Lewicki & Bunker, 1996; Zajac et al., 2000).

Although including a dynamic mediator (or time-varying predictor) in a growth model may appear to be a straightforward procedure, this is not a trivial addition and requires additional conceptual and methodological thought to apply and interpret the models correctly. Scholars must be cautious because the addition of time-varying predictors produces a different type of the classic RCM growth model and a sizeable departure from the commonly used SEM growth model. Perhaps this is why we have found no methodological publications discussing interpretative and application issues with time-varying predictors in the organizational literature.

Singer and Willett (2003) described four types of time-varying predictors: ancillary, contextual, internal, and defined. Ancillary time-varying predictors refer to characteristics of the context in which the participants operate (e.g., unemployment rate, stock market indexes). Contextual time-varying predictors are similar to ancillary ones, except that their change can be affected by a participant's outcome values or the dependent variable in a study. Internal time-varying predictors are typical for organizational research and characterize a participant's changing psychological, physical, or social status over time. Finally, defined time-varying predictors have predefined values for the population studied. They most commonly reflect the passing of time that may be based on minutes, days, months, seasons, or similar time metrics.

It would seem that time-varying predictors are not that different from time itself, but the unique characteristics of each present important conceptual and methodological concerns. In terms of conceptual concerns, realize that only the time-varying predictor correctly represents the dynamic relationship because it models change in X producing change in M and ultimately change in Y. Only by including time-varying predictors can one model dynamic mediation.

In terms of methodological concerns, there are two main issues. First, there is the issue of reciprocal causation between the predictor and outcome. Issues of reciprocal causation are complex, yet with careful specification and testing of models with time-varying predictors, it is possible to provide better tests. Specifically, Singer and Willett (2003) indicate that of the four types of time-varying predictors, only the contextual and internal time-varying predictors are susceptible to reciprocal causation effects. The defined and ancillary time-varying predictors do not have this problem because they are not affected by contemporaneous outcomes. Furthermore, to offset the reciprocal causation concern associated with contextual and internal time-varying predictors, it is suggested that researchers should, first, build their research on a strong theory and, second, code the longitudinal data such that a predictor should be linked to an outcome in a subsequent wave of measurement. This ensures that the predictor always precedes the outcome, even though both are measured at repeated (and possibly identical) time periods. The second methodological concern is with regard to the monotonic nature of the change in the predictor. Not all time-varying predictors will be monotonic over time (Singer & Willett, 2003). If the time-varying predictor does not exhibit monotonic change over time, then one should either also include time in the model (as we illustrated above) or be sure the X (or M) scores precede the M (or Y) scores temporally (e.g., by a time lag). For example, suppose one examines the relationship between performance and self-efficacy over time. If self-efficacy is not monotonic over time, then it is important to include time in the model or ensure that there is a lag such that self-efficacy at time T is linked to performance at time T + 1. Importantly, these issues are relevant for both RCM and SEM, even though there is little discussion of them in the SEM literature.

Finally, it is worth pointing out that the representations of dynamic mediation in RCM and SEM are similar but not identical. In RCM, the model is linking change in one variable to change in another, but not necessarily growth because there is no imposed structure on this relationship (e.g., linear, polynomial, or orthogonal polynomial). It is also true that RCM does not provide as direct a test of mediation as does SEM (James et al., 2006) because like testing mediation with regression, RCM requires a series of steps and tests (see Kenny et al., 2003). In contrast, the SEM approach models dynamic mediation directly because SEM can accommodate multiple X, M, and Y variables simultaneously. However, the SEM approach runs into some technical issues when modeling multilevel, dynamic mediated relationships. Multilevel SEM models are available, but their use has to date been limited.

It is beyond the scope of this article to address all the statistical similarities and differences between RCM and SEM. Given the lack of comparative research, we also do not wish to present one approach as universally more appropriate than another because there is considerable research by methodologists that has used both (e.g., RCM, Maxwell & Cole, 2007; SEM, James et al., 2006). Instead, based on the current state of the literature, we suggest that models for single-level dynamic mediation are probably best modeled via SEM if one hypothesizes that a specific form of growth in X, M, and Y is important. Otherwise, if one simply wants to look at the dynamic relationships between X, M, and Y, then either SEM (without fixing the slope loadings) or RCM is appropriate. However, if the data are multilevel or involve interactions (e.g., dynamic forms of mediated moderation and moderated mediation), then RCM is currently the preferred approach. Again, we emphasize these are tentative suggestions and that both approaches are viable. The field of mediation in longitudinal and multilevel contexts is still young and evolving, and our suggestions are based on the best research available at this time. Clearly, future comparative research is necessary to provide more specific guidance or propose other types of models.

An Empirical Comparison of Dynamic Mediation Modeling to Traditional Approaches

In this section, we illustrate how modeling dynamic mediation provides better tests of theory than cross-sectional approaches. Because the multilevel dynamic longitudinal mediation models are the most complex, we illustrate this type of model using RCM. We also compare the multilevel dynamic mediated results to those of a traditional growth model and a static (cross-sectional) mediation model to demonstrate how the cross-sectional results can be dramatically different than the longitudinal results (as noted in Maxwell & Cole, 2007).

We use an individual performance example, where individuals are nested within teams. Extant motivation theory suggests that changes in effort should be related to changes in performance over time (Kanfer & Ackerman, 1989). In this example, we also take a contextualized view of motivation by further investigating whether there is a cross-level effect of team diversity on changes in performance over time that is mediated by changes in individual effort over time. Thus, we are testing a cross-level dynamic mediation model, where the effect of team diversity (X) on change in individual performance (Y) is accounted for by changes in individual effort (M). Although there are other questions we could examine, for simplicity we focus only on the models necessary to test mediation.

For the purpose of illustration, we are using a subset of data collected as part of a pilot study on antecedents of individual and team performance. The sample consisted of 27 action teams, with each team having between five and seven team members ($N = 151$). There were five measurement waves, and with the exception of diversity, all variables were measured in each time period. Diversity was time invariant because there was no change in team composition during the time period under investigation. A summary of the final models in the three analyses is presented in Figure 3 (we do not show the results of the model-building sequences only to save space).

The Static Model

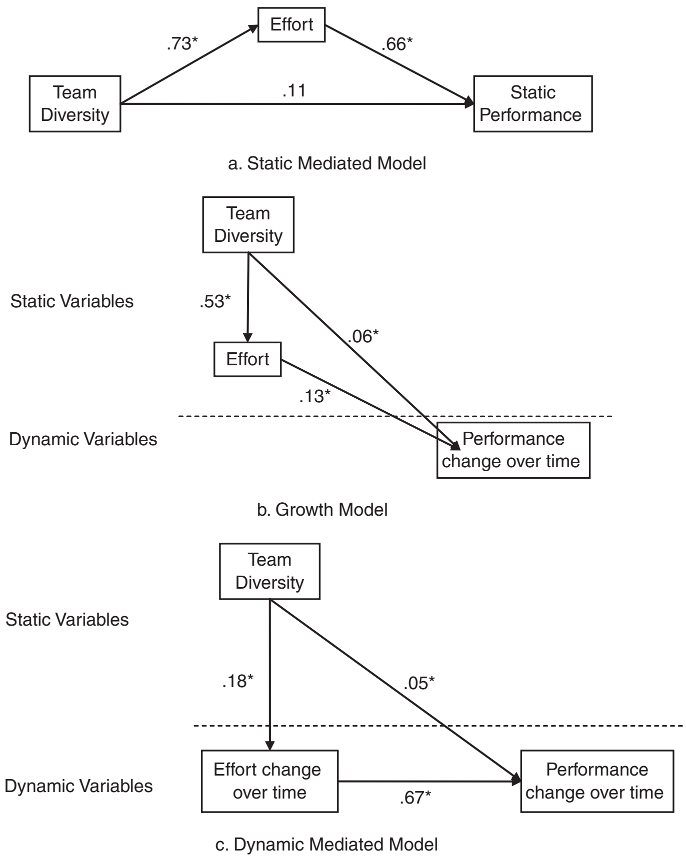
In this first example, we follow traditional practice and ignore the longitudinal and multilevel nature of the theory and data. Consequently, we propose hypotheses that are static and single level such that the effect of diversity on performance is mediated by effort. We then carry out our analyses at the individual level using averages (across time) of the values of both the dependent variable (performance) and the mediator (effort). Following recommendations for testing mediation in regression (Kenny, Kashy, & Bolger, 1998; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002), we first regress performance (Y) on team diversity (X). The effect of team diversity is significant, $F(1, 147) = 28.43$, $b_{TD} = .59$, $p < .01$, indicating that team diversity is positively related to individual performance. Next, we regress effort (M) on team diversity (X) and find a significant positive relationship, $F(1, 147) = 64.04$, $b_{TD} = .73$, $p < .01$. Finally, we add effort (M) to the first equation, which results in a reduced effect of team diversity on performance and a positive and significant effect of effort on performance ($b_{TD} = .11$, *ns*; $b_{Effort} = .66$, $p < .01$). These results, along with a significant Sobel test ($s_{ab} = 5.61$, $p < .01$), provide statistical support for a fully mediated effect of team diversity on individual performance.

In sum, the classic multiple regression approach allowed us to test a static research question about mediation. However, in this framework, we could not test the theory as specified. This suggests we not only used a less informative approach but also one with potentially erroneous conclusions (Maxwell & Cole, 2007).

The Longitudinal Growth Model

In this second example, we make a hypothesis that performance is going to change over time. However, as frequently done, we ignore the dynamic role of the mediator and hence

Figure 3
Summary of Analyses—Final Models for Static, Growth, and Dynamic Mediated Models



make additional hypotheses that diversity and effort are related to performance change over time, with effort mediating the relationship. When testing this model, we consider the dynamic nature of performance over time by modeling performance change via a growth model, following the model-building sequence described by Bliese and Ployhart (2002). The main steps include variance partitioning, determining the fixed functions of time, and determining the variability of the growth parameters.[3] Because the classic growth model cannot handle dynamic mediation, we use an average of the effort measures taken over time. To summarize these analyses, we find that performance follows a linear growth trend characterized by the initial status parameter $\gamma_{intercept} = 4.50$, $p < .01$, and by the slope parameter $\gamma_{slope} = .30$, $p < .01$, and there is significant variability around these parameters. Diversity is grand mean centered in all models.

To test if effort mediates the effect of diversity on performance over time, we follow recommendations by Kenny et al. (1998) and Krull and MacKinnon (1999) for testing static mediation in multilevel models. First, we enter team diversity (X) in the model and find that it has a positive effect on performance change over time ($\gamma_{TD * Time} = .10$, $p < .01$). This means that individuals in teams with greater diversity will improve over time at a faster rate than those in more homogeneous teams. Second, we regress effort (static) on diversity ($b_{TD} = .53$, $p < .01$). Finally, we run a model with both the independent variable (team diversity) and the mediator (effort) and find that the effect of effort on performance over time is statistically significant ($\gamma_{Effort * Time} = .13$, $p < .01$) and the effect of team diversity on performance over time became weaker ($\gamma_{TD * Time} = .06$, $p < .05$). A Sobel test ($s_{ab} = 4.88$, $p < .01$) further confirms the mediated relationship.

In sum, testing static mediation in a growth model finds that effort partially mediates the effect of team diversity on performance over time. However, we have to keep in mind that to perform this analysis we had to make the mediator static. Therefore, we not only fail to fully test the theory presented in this example, but our findings could also be misleading because the model is misspecified (Maxwell & Cole, 2007).

The Dynamic Mediation Model

This final example involves a static higher level independent variable and a dynamic mediator and dependent variable at the lower level. Because we consider the longitudinal and multilevel nature of the theory, our hypotheses can be specified with greater precision. We expect that the effect of team diversity on changes in individual performance is mediated by changes in effort over time. In this particular case, we have to specify a three-level model with Level 1 representing the within-individual effects, Level 2 representing the between-individual effects, and Level 3 representing the between-teams effects. Because this is a multilevel longitudinal model with a static predictor (X), this model is slightly different from that presented earlier (although the basic logic of testing mediation is identical).

The first step for testing mediation requires us to regress change in performance over time onto team diversity. The equations used to test this model are shown below:

$$\text{Level 1: } Y_{tij} = \pi_{0ij} + \pi_{1ij}T_{tij} + e_{tij} \tag{9}$$

$$\text{Level 2: } \pi_{0ij} = \lambda_{00j} + r_{0ij} \tag{10}$$

$$\pi_{1ij} = \lambda_{10j} + r_{1ij} \tag{11}$$

$$\text{Level 3: } \lambda_{00j} = \gamma_{000} + u_{00j} \tag{12}$$

$$\lambda_{10j} = \gamma_{100} + \gamma_{101}X_j + u_{10j} \tag{13}$$

where Y_{tij} is the outcome score of individual i in team j at time t and T_{tij} is the time metric for individual i in team j at time t. The estimated parameters in the Level 1 equation (equation (9)) are π_{0ij}, which is the outcome at time zero; π_{1ij}, which is the change in the outcome because of time; and e_{tij} is the Level 1 error. In the Level 2 equations (equations (10) through (11)), λ_{00j} is the mean intercept (initial status) for all individuals in team *j*, λ_{10j} is the mean slope for time for all individuals in team *j*, and r_{0ij} and r_{1ij} are the respective Level 2 residuals. In the Level 3 equations (equations (12) and (13)), γ_{000} is the mean intercept (initial status) for all teams, γ_{100} is the mean slope for time for all teams, γ_{101} is the change in slope corresponding to one unit change in the predictor *X*, and u_{00j} and u_{10j} are the respective Level 3 residuals.

The focus is on the effect of team diversity on the slope for performance change over time (γ_{101}). Because this model is identical to the model presented in the previous section, we will not describe it again other than to note that diversity has a significant positive effect on the slope of performance over time ($\gamma_{101} = .10$, $p < .01$; see Model 1 in Table 2). Substantively, this means that performance increases more quickly for individuals who are part of more diverse/heterogeneous teams (see Figure 4a).

The second step requires us to regress change in effort over time onto team diversity. The equations used to test this model are identical to the equations used in the first step (equations (9) through (13)), except that the dependent variable is now change in effort. The focus here is on the effect of team diversity on the slope for change in effort over time (γ_{101}). Note that prior analyses found that effort manifests a positive linear trajectory over time ($\pi_{1ij} = .34$, $p < .01$), and there is significant variability in the intercept and slope. We therefore enter team diversity in the model and find it has a significant positive effect on change in effort over time ($\gamma_{101} = .18$, $p < .01$; see Model 2 in Table 2). Substantively, this means that effort increases more quickly for individuals in heterogeneous teams.

The final step requires us to regress change in performance over time onto change in effort over time and team diversity. This model is represented by equations (14) through (20) below:

$$\text{Level 1: } Y_{tij} = \pi_{0ij} + \pi_{1ij}T_{tij} + \pi_{2ij}M_{tij} + e_{tij} \tag{14}$$

$$\text{Level 2: } \pi_{0ij} = \lambda_{00j} + r_{0ij} \tag{15}$$

$$\pi_{1ij} = \lambda_{10j} + r_{1ij} \tag{16}$$

$$\pi_{2ij} = \lambda_{20j} + r_{2ij} \tag{17}$$

$$\text{Level 3: } \lambda_{00j} = \gamma_{000} + u_{00j} \tag{18}$$

$$\lambda_{10j} = \gamma_{100} + \gamma_{101}X_j + u_{10j} \tag{19}$$

$$\lambda_{20j} = \gamma_{200} + u_{20j} \tag{20}$$

where Y_{tij} is the outcome score of individual *i* in team *j* at time *t*, T_{tij} is the time metric for individual *i* in team *j* at time *t*, and M_{tij} is the dynamic mediator (or time-varying mediator) for individual *i* in team *j* at time *t*. The estimated parameters in the Level 1 equation (equation (9)) are π_{0ij}, which is the outcome when all Level 1 predictors (time and dynamic mediator) are zero; π_{1ij}, which is the change in the outcome because of time; π_{2ij}, which represents the change because of the dynamic mediator; and e_{tij} is the Level 1 error. In the Level 2 equations (equations (10) through (12)), λ_{00j} is the mean intercept (initial status) for all individuals in team *j*, λ_{10j} is the mean slope for time for all individuals in team *j*, λ_{20j} is

Table 2
The Effects of Team Diversity (X) and Effort (M) on Performance (Y) Over Time (T)

Effect	Model 1	Model 2	Model 3
Dependent variable	Performance	Effort	Performance
Fixed effects			
Intercept	4.500*	3.008*	2.505*
	(0.250)	(0.076)	(0.257)
Time	0.301*	0.355*	0.069
	(0.052)	(0.029)	(0.053)
Effort			0.666*
			(0.044)
Team Diversity * Time	0.103*	0.176*	0.050*
	(0.023)	(0.015)	(0.019)
Random effects			
Intercept	1.565*	0.043	1.079*
Time	0.053*	0.009†	0.056*
Effort			0.035†
Model fit indexes			
–2LLR	2,051.3	1,689.5	1,816.6
AIC	2,069.3	1,707.5	1,844.6
BIC	2,080.9	1,719.1	1,862.8

Note: LLR = log likelihood ratio; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. Standard errors of estimates are reported in parentheses. Note that we only present the parameters most relevant to testing mediation.
† $p < .10$. * $p < .05$.

the mean slope for the dynamic mediator for all individuals in team j, and r_{0ij}, r_{1ij}, and r_{2ij} are the respective Level 2 residuals. In the Level 3 equations (equations (13) through (15)), γ_{000} is the mean intercept (initial status) for all teams, γ_{100} is the mean slope for time for all teams, γ_{101} is the change in slope corresponding to one unit change in the predictor X, γ_{200} is the mean slope for the dynamic mediator for all teams, and u_{00j}, u_{10j}, and u_{20j} are the respective Level 3 residuals.

The focus is on whether the effect of team diversity on performance change over time weakens relative to the same effect in Model 1 above. Thus, we include change in effort over time along with team diversity in the model.[4] As shown in Table 2 (Model 3), the effect of team diversity on time ($\gamma_{101} = .05$, $p < .01$) decreased by approximately 50% relative to Model 1 (to simplify the presentation, Table 2 only reports the parameters of interest in testing mediation). A Sobel test (9.17, $p < .01$) further supports an inference of mediation (see Figure 4b). Change in effort has a strong positive effect on change in performance over time ($\pi_{2ij} = .67$, $p < .01$).

In sum, we have evidence that the effect of team diversity on changes in performance is partially mediated by changes in effort. Note that some of the parameters produced by this analysis are statistically significant yet substantially different from those produced by the static and growth model analyses. This is consistent with Maxwell and Cole's (2007)

Figure 4a
The Effect of Team Diversity on Individual Performance over Time

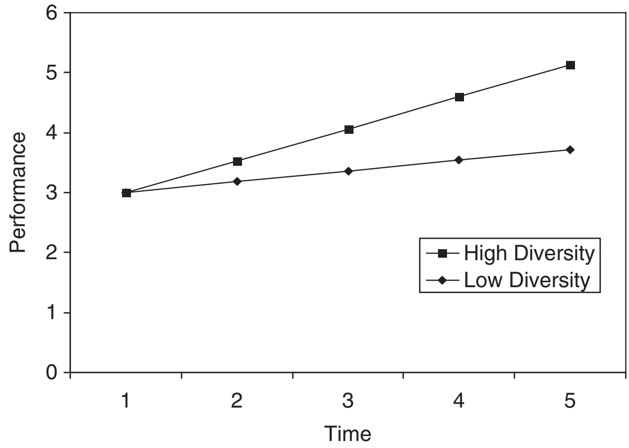
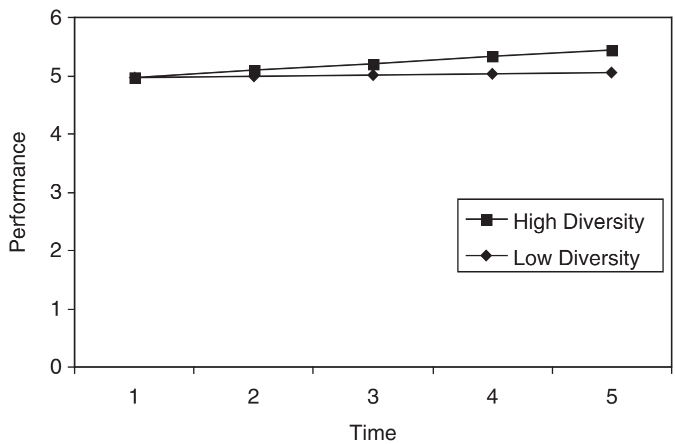


Figure 4b
The Effect of Team Diversity on Individual Performance Over Time, Partially Mediated by Change in Individual Effort Over Time



cautionary note about the biased coefficients produced by cross-sectional analyses when modeling relationships between variables over time. For example, the static research approach concluded full mediation, whereas the growth model and dynamic mediated model concluded partial mediation. Likewise, some of the effect sizes between the growth model and dynamic mediation model differ in substantively important ways. Our example illustrates that if longitudinal data are available, ignoring them and analyzing mediation cross-sectionally may lead to erroneous conclusions (Maxell & Cole, 2007). Thus, the dynamic mediation model overcomes many key limitations of the previous two analytical strategies for modeling dynamic mediated models.

Conclusion

Theories of organizational and management phenomena have become increasingly concerned with modeling dynamic mediated (and frequently multilevel) relationships that evolve over time. Adequately testing these more sophisticated theories requires specifying hypotheses and employing statistical models that use parameterizations consistent with the theory. The issues introduced in this article offer one way to specifically conceptualize and test for dynamic mediation in longitudinal contexts, thereby filling a void in the literature between mediation and longitudinal modeling. When the theory proposes mediators in dynamic longitudinal contexts, the procedures described in this article represent one approach for researchers to more directly hypothesize and test their theories. However, the present study has only scratched the surface of available models for dynamic longitudinal and multilevel mediation, and we encourage others to examine these models to test their hypotheses. This is more than desirable; it is essential to building an empirical database that contributes to developing better theory and enhancing our understanding of relationships between constructs that unfold over time.

Notes

1. This article assumes that readers have a basic familiarity with growth models and a good understanding of Ordinary Least Squares regression (those less familiar may wish to consult Bliese, 2002; Bliese & Ployhart, 2002; Chan, 1998; Cohen, Cohen, West, & Aiken, 2003; Raudenbush & Bryk, 2002). Therefore, we only briefly review growth models to move more quickly into the newer material.

2. These configurations are by no means exhaustive. For example, one could model static mediators. However, given our emphasis on dynamic mediation, we limit our examination to only models with dynamic mediators. It is straightforward to extend these models to the simpler case where the mediator is static.

3. Because of the nature of the research design, we expected that the heterogeneity of the dependent variable would increase over time and that the errors could be correlated. Consequently, we tested several alternative error covariance structures (e.g., autoregressive, autoregressive with heterogeneous error) to check if they might fit better than the unstructured matrix used so far. All other structures resulted in models with poorer fit or in models that did not converge. Therefore, we decided to perform our analysis based on an unstructured error covariance matrix.

4. Prior analyses found that the interaction between time and effort was not statistically significant. For this reason, we only enter the main effects of effort and time in the model.

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