Michael Ahearne, Son K. Lam, John E. Mathieu, & Willy Bolander

Why Are Some Salespeople Better at Adapting to Organizational Change?

This study empirically examines the longitudinal influences of salesperson goal orientations on performance trajectories during a planned change intervention that requires learning to answer two questions. First, what is the functional form of salespeople's performance trajectories during a period of change implementation? Second, why are some salespeople better at adapting to change than others? Polynomial growth models show that the average salesperson performance trajectory displays an initial decline, gradual recovery, and eventual restabilization. Salesperson learning orientation is related positively to larger initial declines, steeper recovery slopes, and higher restabilization levels. In contrast, performance orientation is related positively to smaller initial declines, but shallower recovery slopes and lower restabilization levels. The results suggest that successful implementation of planned change interventions largely depends on identifying and appreciating the heterogeneity of individual traits that share meaning with the change. The study has implications on what sales managers should expect in terms of performance losses and gains during change and how managers can predict which salespeople will reap the largest performance benefits from a change intervention.

Keywords: salesperson, organizational change, adaptation to change, goal orientation, growth modeling

A recent census by the U.S. Bureau of Labor Statistics (2007) reported that there were some 14.5 million people, approximately 10% of the workforce, employed in sales and related occupations. As a result of the large number of people and dollars involved in an organization's sales function, a significant body of marketing literature examining the determinants of salesperson performance has accumulated (e.g., Brown and Peterson 1993; VandeWalle, Cron, and Slocum 2001; Weitz, Sujan, and Sujan 1986). While this research has illuminated understanding of salesperson performance during times of stability, little is known about salesperson performance during periods of organizational change.

"Change is fundamental to a modern business organization as a means to keep up with evolving market demands and to stay competitive" (Ye, Marinova, and Singh 2007, p. 156). Indeed, practitioners and scholars alike agree that change is ubiquitous and can be unexpectedly instigated by external forces, such as competitors or regulators, or strategically initiated by firms to stay competitive (Day 1994), to discard core rigidities (Leonard-Barton 1992), or to improve performance (Chan 2000). As rapid change becomes increasingly descriptive of organizational life and because the battle for successful change implementation is often won or lost with customer-facing employees (Brown 2005), the ability of salespeople to adapt to change, by maintaining and improving performance, becomes critical for both the employees encountering change and the firms that employ them.

This study examines how salespeople adapt to a planned change. While planned change is intended to result in improved performance, it often "simultaneously generates expected performance gain and unexpected performance loss" (Ye, Marinova, and Singh 2007, p. 156). Our research questions are twofold. First, what is the functional form of salespeople's performance trajectories during a period of planned change implementation? Second, and more important, why are some salespeople better at adapting to change than others?

Specifically, we draw from the goal orientation literature and the Lewin–Schein (Lewin 1947; Schein 1964) conceptualization of the phases of planned organizational change to derive hypotheses regarding salesperson performance during times of change. With a unique data set that combines objective longitudinal performance data and surveys, we used hierarchical polynomial growth modeling to investigate the performance trajectories of 400 pharmaceutical sales representatives over 12 months before, during, and after the switch to a new customer relationship management (CRM) system. This type of organizational change is prevalent because firms must periodically re-architect their sales management technology to improve efficiency and stay competitive. Notably, sales forces frequently reject these new technologies (for a seminal discussion, see Davis, Bagozzi, and Warshaw 1989). In predicting how some salespeople are better at adapting to change by resolving tensions between learning and performing, we used salesperson goal orientations because these traits are related to

Michael Ahearne is Professor of Marketing (e-mail: mahearne@uh.edu), and Willy Bolander is a doctoral student in Marketing (e-mail: wcbolander@uh.edu), C.T. Bauer College of Business, University of Houston. Son K. Lam is Assistant Professor of Marketing, Terry College of Business, University of Georgia (e-mail: sonlam@terry.uga.edu). John E. Mathieu is Cizik Chair in Management and Professor of Management, School of Business, University of Connecticut (e-mail: jmathieu@business.uconn.edu). Michael Ahearne, Son K. Lam, and John E. Mathieu contributed equally to this article.

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how people interpret achievement situations and how they are intrinsically and extrinsically motivated to learn, unlearn, and perform (Kohli, Shervani, and Challagalla 1998).

The findings show that the average salesperson performance trajectory displayed an initial decline, gradual recovery, and eventual restabilization during the planned change intervention. Salesperson goal orientations—namely, learning and performance orientations (hereinafter, LO and PO, respectively)—related to initial declines, recovery slopes, and restabilization levels in a countervailing manner. In addition to addressing important substantive issues for marketers and marketing scholars in the area of organizational change and salesperson adaptation, this study responds to multiple calls by organizational researchers for increased consideration of the role of both time (Armenakis and Bedeian 1999) and individual employee dispositions (Bray 1994; LePine 2003) when studying change. By demonstrating what sales managers should expect in terms of performance losses and gains and how managers can predict which salespeople will reap the largest performance benefits from a change intervention, this study has important managerial implications regarding how managers can predict and improve salesperson adaptation.

In the next section, we briefly review the Lewin–Schein theory of change along with the goal orientation literature to develop the research hypotheses. We then present the empirical findings. We conclude with managerial implications and future research directions.

Background and Hypotheses Development

Change researchers have long recognized the importance of time, often pointing out that conclusions drawn from research that is indifferent to the effect of time can be misleading because relationship stability may be mistakenly assumed (Armenakis and Bedeian 1999; Van de Ven and Poole 1988). More important, change processes may be inherently nonlinear (Beer and Walton 1987). These viewpoints are consistent with Lewin's (1947) theory of change, which consists of three phases: unfreezing, moving, and refreezing. Schein (1964) elaborates the underlying mechanisms of these phases from the perspective of interpersonal dynamics. Next, we discuss the Lewin–Schein theory of change in relation to individual performance trajectories. Consistent with the change literature, we refer to people undergoing the change as "change targets."

The Lewin–Schein Theory of Change

Lewin's (1947) first phase of change is the unfreezing phase, during which a relatively stable level of performance is thrown into a flux by a change event. Schein (1964) suggests that the unfreezing phase occurs through the disconfirmation of beliefs and behavior and a belief that change is possible, or psychological safety. Essentially, the first phase is characterized by unlearning (Schein 1964, p. 365). Consider a salesperson being confronted with a planned organizational change. After entering the unfreezing period, change targets are normally required to crawl out of their comfort zone to ask questions, seek help, experiment, and speak up about their concerns. These activities are related to the unlearning of past routines (Schein 1964), heightened interpersonal risks (Edmonson, Bohmer, and Pisano 2001), anxiety (Schein 1964), and uncertainty (Burkhardt and Brass 1990). These processes cause stress and take time away from the normal performance activities. The unfreezing phase then should be associated with an immediate performance drop.

Lewin's (1947) second phase of change is the moving phase. Whereas the unfreezing phase is best viewed as a sudden shock, the moving phase represents a gradual shift to some semistable end state. Following the initial disturbance caused by the change, a salesperson should begin taking proactive steps toward adaptation by "conceptualizing a problem, acquiring information about relevant forces, locating or developing alternative solutions, and choosing a course of action" (Zand and Sorensen 1975, p. 535). Schein (1964) refers to these processes as "cognitive redefinition." Cognitive redefinition facilitates the shift from the moving phase to the subsequent refreezing phase as long as the change target is open to and capable of proactively using and assimilating new sources of information. For a salesperson, a particularly interesting aspect of the moving phase is the conscious trade-off made between spending time selling and spending time learning to adapt. As the change target adapts, performance gains are realized because his or her time allocation shifts from learning to producing, in addition to any benefits that result from implementing the change itself. Furthermore, uncertainty should diminish during the moving phase, enabling change targets to allocate less time to struggling with new processes (Burkhardt and Brass 1990). As a result, the change target's performance should show evidence of an upward recovery trend during the moving phase.

Finally, Lewin's (1947) third phase is the refreezing phase, which results when performance stabilizes again, hopefully at a higher level than before the intervention. Change researchers have underscored the notion that "the mechanism by which the change is induced in the first place has consequences for the ease or difficulty of refreezing" (Schein 1964, p. 388). For example, if change targets actively engage in information acquisition and assimilation during the moving phase, the subsequent self-selected solutions will be more readily integrated into their existing knowledge, producing success levels that are not only higher but also more stable (Schein 1964). There are at least three reasons for this performance stabilization. First, diminishing returns on learning might kick in when sufficient time has elapsed since the initiation of change. Second, the change target might move past the initial negative reaction to the change. Third, the change target might become more comfortable with postintervention work when he or she has learned and formed new habits and routines that are "confirmed" as appropriate and effective for the new environment (Schein 1964; Zand and Sorensen 1975). Thus, we hypothesize the following:

> H_1: Following a planned change intervention, the average performance trajectory of a salesperson exhibits (a) an initial

performance decline, then (b) a positive recovery, and (c) an eventual leveling off of performance.

Goal Orientations as Determinants of Adaptation

Goal orientations have been defined as the "disposition toward developing or validating one's ability in achievement settings" (VandeWalle 1997, p. 995). Goal orientations are also theorized to be the means by which higher-level goals (e.g., esteem, affiliation) are achieved (DeShon and Gillespie 2005) and the drivers of individual behavior, such as learning and skill development (VandeWalle 1997). Because organizational change presents an achievement opportunity and because achievement constitutes a major part of personal selling, salespeople's goal orientations are particularly relevant dispositions that are likely to influence their performance during a change. Furthermore, our application of goal orientations in the context of change serves as a response to Bray's (1994) call for increased consideration of the effect of individual traits in research on organizational change (see also Bryk and Raudenbush 1987; Chan 2000).

It is widely recognized that there are two types of goal orientation: learning and performance-prove orientation, or as previously defined, LO and PO. Recent research has distinguished between PO, which orients people to behave in an effort to be recognized as achieving performance superior to others, and performance-avoid orientation (AO), which orients people to behave in an effort to avoid negative performance evaluation (Elliot and Harackiewicz 1996; VandeWalle 1997; VandeWalle, Cron, and Slocum 2001). We do not discuss AO in this study for three reasons. First, goal orientation research in marketing and sales has traditionally focused solely on PO and LO (Kohli, Shervani, and Challagalla 1998; Sujan, Weitz, and Kumar 1994). Second, not all empirical results have so firmly implicated AO as the dysfunctional aspect of goal orientation. For example, in an experimental setting, Elliot and Harackiewicz (1996) find that AO has no negative effect on task performance, despite its negative effect on intrinsic motivation. Third, AO was initially included in our analysis but failed to produce a significant effect on salespeople's performance trajectories. Therefore, all references to performance orientation in this text refer specifically to PO.

Learning orientation "orients people to improve their abilities and master the tasks they perform," whereas PO orients people to "achieve a positive evaluation of their current abilities and performance from important others" (Sujan, Weitz, and Kumar 1994, p. 39). Although prior research has viewed LO and PO as opposite ends of a continuum, more recent evidence indicates that they are two distinct constructs (Button, Mathieu, and Zajac 1996; Sujan, Weitz, and Kumar 1994). Importantly, although much research has explored goal orientations, mixed findings abound regarding the relationship between salesperson goal orientations and performance. Existing results range from a strong and positive relationship (Sujan, Weitz, and Kumar 1994) to no relationship (Kohli, Shervani, and Challagalla 1998). The notion that these conflicting results can be resolved by considering the interaction between goal orientations and time has been suggested by some (e.g., Kohli, Shervani, and Challagalla 1998; Payne, Youngcourt, and Beaubien 2007). We subject the longitudinal relationship between these goal orientations and performance during learning-related change to empirical scrutiny.

LO. The key element of LO is a person's strong intrinsic desire to improve his or her skills for the sake of being able to do things better by allowing him- or herself to "develop skills and abilities that are beneficial over a longer period of time" (Kohli, Shervani, and Challagalla 1998, p. 271). Payne, Youngcourt, and Beaubien (2007) also suggest that people high in LO engage in "deep" learning strategies (see also Elliot and Harackiewicz 1996). Such people use obstacles as a cue to increase their effort, consider mistakes part of the learning process, and place high value on personal growth (Dweck 1986, p. 1042).

The combination of the Lewin–Schein theory of change and the goal orientation literature suggests that people with a strong LO are more likely to unfreeze at a faster rate because they unlearn faster and consider feedback seeking less costly and more valuable (VandeWalle, Cron, and Slocum 2001). Such people seek to disconfirm prior beliefs and forsake ineffective behavior earlier than their low-LO counterparts. High-LO targets also possess a "can-change" attitude, and as a result, they are more likely to embrace the challenge of change without much fear or anxiety. Because high-LO change targets engage in deep learning, their investments in mastering new knowledge and unlearning in the unfreezing phase are more likely to pay off in the moving phase. Finally, compared with low-LO people, high-LO people are more poised to identify effective learning strategies that are crucial in reaching a higher level of performance during the refreezing phase (Zand and Sorensen 1975). This suggests the following:

H_2: Following a planned change intervention, compared with low-LO salespeople, the performance trajectory of high-LO salespeople exhibits (a) a larger initial performance decline, (b) a steeper positive recovery, and (c) a higher eventual level of performance.

PO. Performance orientation is primarily manifested in a person's desire to be viewed positively relative to others through the demonstration of his or her current ability. Previous research has shown that a high-PO person is extrinsically motivated and primarily focused on the present (Kohli, Shervani, and Challagalla 1998). Together, the goal orientation literature and the Lewin–Schein theory of change suggest that during the unfreezing phase, high-PO people experience a smaller decrease in their performance than low-PO people. Change targets who are primarily driven by PO experience some performance drop because they take time to learn and adapt to the change since they believe that doing so will contribute to their performance. However, those with a strong PO engage in "shallow" learning, prefer a functional understanding to an expert understanding, and allocate less time to learning (Payne, Youngcourt, and Beaubien 2007). Such people seek "normative competence" (Porath and Bateman 2006, p. 186).

Given that high-PO change targets use shallow learning strategies to lessen their initial performance drop, their rate of recovery during the moving phase will be lower for two primary reasons. First, these change targets must ultimately devote time to learning to adapt so that they can maintain an acceptable level of performance relative to early adopters, who might now excel over them. Second, because high-PO change targets are extrinsically motivated, they are more likely to be occupied with passive and other-directed behaviors, and their adaptation might not be highly effective. Finally, because of the lack of significant learning immediately following the unfreezing phase, a high-PO person will ultimately have a difficult time "catching up" and will arrive at a lower performance level approaching the refreezing phase. This suggests the following:

> H_3: Following a planned change intervention, compared with low-PO salespeople, the performance trajectory of high-PO salespeople exhibits (a) a smaller initial performance decline, (b) a flatter positive recovery, and (c) a lower eventual level of performance.

Method

Overall Study Context

The adoption of sales technologies, such as a CRM system, is an important area of change in sales management. The worldwide CRM market has doubled in recent years, exceeding revenues of $7 billion (Bailor 2007). Although sales technology adoption is an entrenched research area (e.g., Davis, Bagozzi, and Warshaw 1989; Hunter and Perrault 2007), research on the ups and downs of salesperson performance during postadoption processes, such as technology utilization, upgrade, and change, remains sparse (Ahearne et al. 2008). Accordingly, our focus is on sales technology change. Sales technology change is disruptive to salesperson performance in a unique way because (1) sales technology plays a central role in transforming salesperson inputs into important customer-related outputs, (2) new technology represents a learning opportunity that has the potential to affect performance over time, and (3) salespeople are always under pressure to achieve higher performance, leading to a particularly salient tension between learning and performing when adaptation to new situations is required. Because salespeople are the revenue-generating employees of the organization, these issues have direct implications on a firm's bottom line.

Sample and the Change Context

We collected data from a division of a major U.S. pharmaceutical company that was introducing a new suite of sales technology tools to its sales force. Sales representatives in this division were responsible for detailing to physicians in their assigned territory.

The change context. The change context was best described as the transition from a homegrown contact management system to a full-scale process-driven sales force automation system. The change started with training sessions six months before the actual rollout of the new system. The distinction between these two systems was far from subtle, and the impact of this technology change on the sales force was highly disruptive.

The old system was essentially a passive database that stored information on sales meeting history, including notes and product samples provided to the physicians. The new suite of software not only offered these same contact management features but also allowed for active, automated information processing and provided dramatic improvements in terms of route planning, competitive information (e.g., prescription-writing trends of the salesperson's product versus competitive products), multichannel coordination (e.g., centralizing physician-related information obtained from the salesperson, company call center, and company Web site), and the ease with which salespeople could run periodic reports for their managers.

Use of these advanced features required a great deal of training and represented a significant increase in the time the salesperson spent entering data. For example, following a sales call, a salesperson would need to enter notes specifically focused on the result of the meeting, objections that arose during the meeting, and the objective for the next meeting. Furthermore, it was essential that the user knew not only what information to enter but also how it should be entered (i.e., the process). Under the old system, the salesperson would merely check the meeting off of the task list and enter whatever notes he or she viewed as personally relevant. After properly learned and routinized, however, the new system offered efficiency benefits that enabled the user to increase his or her performance. These efficiency gains made up for the extra time spent on data entry because a multitude of the salesperson's decisions and planning activities were now fully automated by the new system. For example, rather than spending time at the beginning of each day deciding which physicians to call on, the order in which to visit them, and which products to focus on, the salesperson was able to rely on the new system to generate his or her daily call schedule, plan the optimal route, provide competitive prescription-writing trends, and provide customized printouts describing previous meetings with the customer (including multichannel contacts) down to assessment of the physician's personality, office atmosphere, and common objections. All this information would be generated automatically, and assuming adequate learning occurred, these efficiency gains provided the opportunity for performance improvements that more than compensated for the increased data entry requirement.

Data collection. We administered surveys in the month preceding the actual sales technology rollout. Surveys were sent to 449 salespeople in a specialty division of a major pharmaceutical company. We then paired the survey participants with their archival performance data. In total, we had complete information from 400 salespeople, for an effective response rate of 89%. Incomplete data were attributable to people failing to respond to the survey or missing performance data. Supplemental analyses showed that this subsample did not differ significantly from the total sample on any study variables. The study sample comprised approximately 52% women, and the median age was approximately 30 years. Respondents' average experience in a sales job was 11.1 years (SD = 8.3), their average tenure within the company was 6.2 years (SD = 6.2), and they had worked in their territories an average of 3.6 years (SD = 4.3).

Most important, the data and the context of the change satisfy the conditions for studying change—namely, (1) multiple waves of data, (2) a continuous outcome that changes systematically over time, and (3) a sensible metric for time (Singer and Willett 2003). Moreover, the preannouncement of the CRM technology switch serves as the initiation of the unfreezing phase. The time surrounding the actual launch of the new CRM suite represents the moving phase, and this subsequently leads to the refreezing phase.

Measures

Goal orientations. We measured salesperson goal orientations using seven-point Likert scales adapted from Sujan, Weitz, and Kumar (1994). We measured LO with six items (α = .76) and PO with four items (α = .70). Confirmatory factor analyses showed that these items loaded on their intended factor. Constraining the correlation of the two constructs to unity resulted in significantly worse model fit ($\Delta\chi^2$ [d.f. = 1] = 90.5, $p < .00$), suggesting that the two constructs had discriminant validity.

Sales performance. We collected sales performance, relative to quota, from the corporate archive for 12 months, covering the month when training started through 6 months after the roll-out. The pharmaceutical firm had a consulting firm set its quota system for the whole year. We used sales to quota for several reasons. First, the consulting firm calculated quota using extensive historical data, salesperson variables, and market forecasts. Therefore, this quota-based performance controlled for seasonality, differences in salesperson skills, sales territories, competitors, and other potential confounding factors to measure true salesperson performance. Second, sales quotas have been shown to be a good objective measure of salesperson job effectiveness (Churchill et al. 1985; Zoltners, Sinha, and Lorimer 2006), with a long history of successful application in the marketing and sales literature (e.g., MacKenzie, Podsakoff, and Fetter 1993; Ross 1991; Zoltners, Sinha, and Lorimer 2006). Third, because sales quota is one of the most important performance criteria and motivators for salespeople (Ross 1991) and because it reflects what salespeople actually did rather than what they could do, it is a better criterion variable in the context of adaptation to change (Chan 2000). The firm did not have its quota adjusted specifically because of the change, since it did not anticipate the change to be highly disruptive. Average sales quota performance rose significantly from the baseline period when training started to the postintervention period (baseline period: M = .96, SD = .09; postintervention period: M = .99, SD = .25; $t(399) = 2.53$, $p < .05$).

Covariates. We controlled for three important factors that may influence salesperson adaptation to technology change and performance: openness to change, work experience, and previous use of sales technology. Openness to change is one of the Big Five personality traits; it captures the extent to which a person is intellectually intrigued by new situations and is amenable to new ideas (Barrick and Mount 1993). We measured individual openness to change with a seven-item, seven-point Likert scale (α = .70) adapted from the personal characteristics inventory (for a full description, see Barrick and Mount 1993). Example items include the following: "I spend time reflecting on things," "I am quick to understand things," and "I prefer variety to routine." Work experience was indexed as the average of a salesperson's years (1) in sales, (2) with the company, and (3) in a particular territory (α = .80). We formed a composite experience measure by averaging z-scores of the three indexes. We assessed previous use of sales technology using four seven-point Likert items that asked how much each salesperson used each of the four facets of the sales technology system: (1) targeting, (2) planning, (3) scheduling, and (4) reporting (α = .80). We averaged item responses to form a summary score.

Analytical Procedure

The data in this study followed a two-level framework. Sales performance constituted an intraperson, or temporally varying, measure (i.e., Level 1, with 12 repeated measures) that was subject to the interperson (i.e., Level 2) influences of the two goal orientations. We employed random coefficients growth modeling techniques in the form of hierarchical multivariate linear modeling (HMLM; see Raudenbush and Bryk 2002) to test our hypotheses. We briefly describe the analytical procedure here and provide further details in the Appendix.

The Level 1 (within-subject, or intraperson) model uses time-related variables to predict changes in the outcome variable. In this study, sales performance trajectories (Y_{ij}) are a function of the linear (t) and potential higher-order quadratic (t^2) and cubic (t^3) time trends. We centered time at the start of the change when training began; thus, the intercept term represents performance of an average salesperson at the start of the period observed. We standardized the Level 2 predictors to facilitate interpretation.

The time-series nature of performance means that within-subject errors will exhibit some degree of autocorrelation (Bliese and Ployhart 2002). Thus, we first modeled the influences of linear, quadratic, and cubic temporal trends on the Level 1 performance, and then we examined alternative models of their error variances (Bliese and Ployhart 2002; Singer and Willett 2003). In this regard, HMLM not only provides a statistical test of the general time-related trends exhibited within each salesperson but also reports a deviance statistic that follows a chi-square distribution. These deviance scores can be used to perform nested model contrasts to test whether temporal patterns are homogeneous across individual salespeople. Notably, heterogeneity of one or more Level 1 temporal parameters is a prerequisite for modeling Level 2 effects. The use of this longitudinal design and growth modeling technique enables researchers to test such hypotheses, which would not be feasible with more traditional regression or repeated mea-

TABLE 1
Correlation Matrix

Variables	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Covariates																		
1. Openness to change	5.79	.70	.70															
2. Experience	.08	.87	–.050	.80														
3. Previous use of sales technology	4.48	1.20	.188	.022	.80													
Salesperson Goal Orientations																		
4. Salesperson LO	6.41	.63	.518	–.116	.145	.76												
5. Salesperson PO	6.18	.75	.376	–.086	.106	.527	.70											
Intraperson Performance Growth																		
6. Prelaunch performance t = 0[a]	1.00	.18	.044	–.059	.065	.009	.005											
7. Prelaunch performance t = 1	.97	.15	.044	–.018	.069	–.047	–.013	.431										
8. Prelaunch performance t = 2	.86	.17	.005	–.008	.033	–.057	.013	.489	.530									
9. Prelaunch performance t = 3	.99	.14	–.016	.067	.078	.047	.129	.055	.107	.208								
10. Prelaunch performance t = 4	.97	.14	.053	.067	–.034	.085	.115	–.010	–.007	.143	.444							
11. Prelaunch performance t = 5	.97	.15	.006	.078	.038	.100	.101	.001	–.057	.092	.505	.518						
12. Postlaunch performance t = 6	1.01	.20	.045	–.043	–.001	.052	.009	–.044	–.074	–.003	.204	.360	.527					
13. Postlaunch performance t = 7	1.05	.24	.014	–.025	–.009	.094	.024	–.063	–.061	–.055	.279	.383	.412	.714				
14. Postlaunch performance t = 8	1.11	.27	–.009	–.055	.009	.043	.020	.058	.049	.090	.123	.157	.187	.287	.327			
15. Postlaunch performance t = 9	1.16	.47	–.017	.012	.023	.046	–.004	.127	.191	.176	–.034	–.024	.019	.070	.120	.507		
16. Postlaunch performance t = 10	1.11	.39	.005	–.024	.035	.072	.028	.118	.177	.161	.046	–.006	.106	.161	.204	.595	.826	
17. Postlaunch performance t = 11	1.02	.33	–.012	.021	.082	.077	–.012	.112	.176	.144	.078	.059	.205	.290	.366	.556	.740	.877

[a]Training started in this month.
Notes: $|r| \geq .14$, $p < .01$; $|r| \geq .11$, $p < .05$. n = 400. Cronbach's α is on the diagonal. Performance data are objective measures of sales quota achievement.

sures analyses (see Bliese and Ployhart 2002; Bryk and Raudenbush 1987).

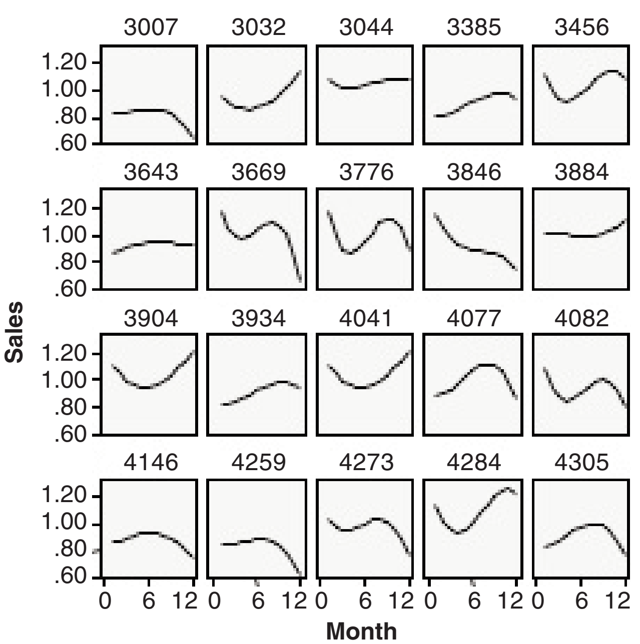
Results

Correlations. Table 1 presents correlations and descriptive statistics for all study variables. In general, neither salespeople's experience nor their use of prior technology exhibited any significant correlations with performance over time. Both LO and PO evidenced some modest but significant and positive correlations with sales performance in the months surrounding the intervention. In summary, the zero-order correlations suggested that few relationships existed between the two types of goal orientations and performance. However, interperson results such as these may fail to reveal the underlying dynamics. Furthermore, pairwise correlations are based on the assumption of linear relationships, which might not necessarily be true in this case if our theoretically derived hypotheses are supported.

Baseline analyses. As an exploratory step, we first plotted the performance trajectories of a random sample of 20 salespeople using smoothing lines. The plots in Figure 1 exhibited significant heterogeneity across these salespeople, but a well-defined pattern of three phases of change—unfreezing, moving, and freezing—emerged.

We then proceeded with formal data analysis. Taken as a whole, we calculated that 79% of the total variance in salesperson performance resided within subjects (over time), and 21% of the total variance resided between subjects. Adding a fixed (i.e., consistent across salespeople) linear trend to the within-subjects model yielded a significant model improvement ($\Delta\chi^2(1) = 230.27$, $p < .001$), though adding the fixed quadratic trend did not ($\Delta\chi^2(1) = 2.37$, n.s.). However, adding a fixed cubic trend produced a significant increase in accounted-for variance ($\Delta\chi^2(1) = 182.82$, $p < .001$). Collectively, the three temporal trends accounted for approximately 24% of the total variance in sales performance over time. Far more important for testing our hypotheses was the variability of these performance trajectories.

FIGURE 1
Stylized Salesperson Performance Trajectories During the Change



Notes: Smoothed performance trajectories of 20 randomly selected salespeople during the change. The numbers at the top of each plot are the employee identification numbers. Vertical axis: 1.00 denotes 100% sales quota achievement.

Nested model contrasts between fixed and random trajectories illustrated that significant variability was evident for each of the Level 1 parameters. Specifically, from the base model, we discerned that the individual intercepts varied significantly ($\chi^2 = 1662.52$, $p < .001$). Next, we added a fixed linear term ($\chi^2(4) = 12{,}839.54$), which when allowed to vary freely ($\chi^2(6) = 11{,}551.98$) evidenced a significant model improvement ($\Delta\chi^2(2) = 1375.25$, $p < .001$). Similarly, adding a fixed quadratic term yielded a model ($\chi^2(7) = 11{,}548.54$) that improved significantly ($\Delta\chi^2(3) = 381.85$, $p < .001$) when permitted to vary freely ($\chi^2(10) = 11{,}216.15$). Finally, adding a fixed cubic trend ($\chi^2(11) = 10{,}897.25$) also yielded a model that improved significantly ($\Delta\chi^2(4) = 161.92$, $p < .001$) when permitted to vary freely ($\chi^2(15) = 10{,}735.33$). These results indicate that different salesperson performance trajectories were evident, which enabled us to test our hypotheses. The random linear, quadratic, and cubic trends accounted for approximately 21%, 8%, and 1% of the interperson variance over time, respectively. This translates to approximately 40% of total sales performance variance within and between subjects (Raudenbush and Bryk 2002; Snijders and Bosker 1999).

We mentioned that because of the temporal nature of the Level 1 data, error terms associated with adjacent months are more likely to be correlated (for details, see the Appendix). We performed a series of nested model tests and determined that an unrestricted error term structure fit significantly better than the homogeneous ($\Delta\chi^2(67) = 4481.30$, $p < .001$), autoregressive ($\Delta\chi^2(66) = 4481.30$, $p < .001$), or heterogeneous ($\Delta\chi^2(56) = 3719.29$, $p < .001$) structures, respectively. We also used Akaike's information criterion (AIC) and Bayesian information criterion (BIC) to evaluate the models (AIC = –2LL + 2K, BIC = –2LL + K.ln[n], where –2LL is the deviance statistic, K is the number of parameters being estimated, and n is the sample size). These two criteria "penalize" models with potential excesses in the number of estimated parameters. We found that the unrestricted model has the lowest AIC and BIC. Therefore, we employed an unrestricted error matrix in the remaining analyses (for further details, see Bliese and Ployhart 2002; Raudenbush and Bryk 2002).

Hypothesis tests. Table 2 presents a summary of the equations estimated for performance trajectories and the HMLM results in unstandardized coefficients. We first regressed the performance intercept and three temporal trends simultaneously onto three covariates: openness to change, experience, and previous technology use. As the "Covariates Only" columns of Table 2 depict, all covariates except previous use of sales technology failed to account for significant variance in the overall performance trajecto-

TABLE 2
Hierarchical Linear Modeling Results

A: Model Specification

Model Specification

Level 1 $Y_{ti} = \pi_{0i} + \pi_{1i}t + \pi_{2i}t^2 + \pi_{3i}t^3 + e_{ti}$

Level 2

$$\pi_{0i} = \beta_{00} + \beta_{01}(OC_i) + \beta_{02}(EXP_i) + \beta_{03}(USE_i) + \beta_{04}(LO_i) + \beta_{05}(PO_i) + r_{0i}$$
$$\pi_{1i} = \beta_{10} + \beta_{11}(OC_i) + \beta_{12}(EXP_i) + \beta_{13}(USE_i) + \beta_{14}(LO_i) + \beta_{15}(PO_i) + r_{1i}$$
$$\pi_{2i} = \beta_{20} + \beta_{21}(OC_i) + \beta_{22}(EXP_i) + \beta_{23}(USE_i) + \beta_{24}(LO_i) + \beta_{25}(PO_i) + r_{2i}$$
$$\pi_{3i} = \beta_{30} + \beta_{31}(OC_i) + \beta_{32}(EXP_i) + \beta_{33}(USE_i) + \beta_{34}(LO_i) + \beta_{35}(PO_i) + r_{3i}$$

B: Estimation Results

	Intercept (π_{0i})		Linear Trend (π_{1i})		Quadratic Trend (π_{2i})		Cubic Trend (π_{3i})	
Predictors	**Covariates Only**	**Full Model**	**Covariates Only**	**Full Model**	**Covariates Only**	**Full Model**	**Covariates Only**	**Full Model**
Intercept	1.0443	1.0444	–.0427	–.0428	.0064	.0065	–.0003	–.0003
	(.0082)**	(.0082)**	(.0050)**	(.0049)**	(.0008)**	(.0008)**	(.00003)**	(.00003)**
OC	.0059	.0044	–.0015	–.0008	.0002	–.0000	–.0000	.0000
	(.0084)	(.0097)	(.0051)	(.0059)	(.0008)	(.0010)	(.00004)	(.00005)
EXP	–.0079	–.0077	.0063.	.0063	–.0009	–.0008	.0000	.0000
	(.0082)	(.0083)	(.0050)	(.0050)	(.0008)	(.0008)	(.00004)	(.00004)
USE	.0175	.0172	–.0086	–.0085	.0013	.0012	–.00005	–.00005
	(.0083)*	(.0084)*	(.0051)*	(.0051)*	(.0009)	(.0009)	(.00004)	(.00004)
LO		.0063		–.0099		.0023		–.0001
		(.0111)		(.0067)		(.0011)*		(.00005)*
PO		–.0045		.0119		–.0023		.0001
		(.0102)		(.0061)*		(.0010)*		(.000048)*

**p* < .05 (one-tailed tests).
***p* < .001 (one-tailed tests).
Notes: Y = sales performance per quota, OC = openness to change, EXP = experience, and USE = previous technology use. Cells depict unstandardized parameter estimates, and values in parentheses are standard errors. i = individual, n = 400, t = 0, …, 11. For the unrestricted model, the between-subjects variation is incorporated in the Level 1 error structure (Raudenbush et al. 2001).

ries ($\Delta\chi^2(12) = 10.39$, n.s.). Inspection of the individual parameter estimates revealed that only previous use of technology significantly and positively influenced the intercept ($\beta = .0175$, $p < .05$) but significantly and negatively influenced the linear trend ($\beta = -.0086$, $p < .05$).

This covariates-only model provided strong support for the anticipated performance trajectory advanced in H_{1a}–H_{1c}. More specifically, the cubic trend was negative ($\pi = -.0003$, $p < .001$), suggesting a downward sloping pattern at the initial stage, as we predicted in H_{1a}. In support of H_{1b}, the quadratic trend was positive ($\pi = .0064$, $p < .001$), suggesting a positive recovery from the previous decline as time progressed farther from the initiation of training. Although the linear trend was significantly different from zero ($\pi = -.0427$, $p < .001$), as time progressed, the opposite signs of the slope of the cubic and quadratic terms suggested that after the intervention, the average performance trajectories would be mainly determined by the countervailing effects of these quadratic and the cubic trends.

Because we centered time scores at the start of the planned change when training began, all the time scores were positive after the first month. The plateau effect, as predicted in H_{1c}, would be supported if the performance trajectory exhibited diminishing returns (rather than increasing returns) as time elapsed after the intervention such that performance gains slowed down after recovery. To test H_{1c}, we examined the sign of the second derivative of the performance trajectory during the refreezing phase, $d^2Y/dt^2 = 6\pi_3 t + 2\pi_2$, evaluated at $t > 0$ because it captured the curvature of the trajectory (i.e., the rate of change of the slope itself). H_{1c} would be supported if, given $t > 0$, $(6t)\pi_3 + (2)\pi_2$ becomes more negative. From the estimated parameters in Table 2 for the slopes of the quadratic and cubic terms, we can intuitively observe that when the time score passed $t = 8.5$ (i.e., the inflection point), this rate of change of the slope became negative. More formally, as long as the cubic trend was significantly negative and the quadratic trend was significantly positive, when the time scores became larger, the diminishing-return phenomena would kick in. We conducted this multivariate test by simultaneously constraining the slopes of both the cubic and the quadratic terms to zero. The fit of the constrained model was much worse than that of the unconstrained model ($\Delta\chi^2(2) = 76.74$, $p < .00$). Thus, in support of H_{1c}, the performance trajectory of an average salesperson plateaued during the refreezing phase.

Next, we added the two goal orientations simultaneously to the performance intercept and three temporal parameters equations. As the "Full Model" columns of Table 2 depict, these goal orientations interacted with time to explain significant variance in the overall performance trajectories. Inspection of the individual parameter estimates revealed that previous use of technology remained significant and positively influenced the intercept ($\beta = .0172$, $p < .05$) and negatively influenced the linear term ($\beta = -.0085$, $p < .05$). Although the goal orientations did not influence the magnitude of the intercept, PO exerted significant, positive effects on the linear trend ($\beta = .0119$, $p < .05$), while LO did not have an influence on this linear trend ($\beta = -.0099$, n.s.). H_{2a}–H_{2b} and H_{3a}–H_{3b} referred to the influence of goal orientations on the slope coefficients of the performance trajectory during the unfreezing and the moving phases. The results support these hypotheses. Specifically, LO added a significant, negative influence on the negative cubic trend ($\beta = -.0001$, $p < .05$), which was the driving force of the decline of the polynomial during the initial stage. Therefore, the results support H_{2a}. As H_{2b} predicted, LO contributed a significant, positive influence on the positive quadratic trend ($\beta = .0023$, $p < .05$), which was responsible for pushing the performance trajectory to recover from the performance trough. Conversely, PO exerted a positive influence on the slope of the cubic term ($\beta = .0001$, $p < .05$) and a negative impact on the slope of the quadratic term ($\beta = -.0023$, $p < .05$). In other words, salespeople with higher PO exhibited a smaller initial performance decline during the unfreezing phase but a flatter positive recovery in the moving phase, in support of H_{3a} and H_{3b}.

As we mentioned in testing H_{1c}, the eventual level of performance leading into the refreezing phase was mostly determined by the countervailing effects of the positive quadratic and the negative cubic trends in determining the curvature. The intuition is that when the slope of the quadratic term is larger than that of the cubic term, at any same point immediately after the performance trough, the recovery will take place at a faster, positive rate (i.e., the curvature turns positive) before diminishing returns kick in (i.e., the curvature becomes negative). Thus, the performance trajectories would climb to higher maxima. In other words, support for H_{2c} and H_{3c} exists if the positivity of the quadratic trend is enhanced (impaired) by LO (PO) and the negative (positive) impact of LO (PO) on the cubic trend is smaller than the positive (negative) impact of LO (PO) on the quadratic trend, respectively. Together, this means that the impact of LO and PO on the recovery process (i.e., through the quadratic trend) is more potent than their respective countervailing effects on the diminishing-return process (i.e., through the cubic trend) before the maxima is reached, thus creating differential plateaus during the refreezing phase. The full model in Table 2 shows that both of these conditions existed, in support of H_{2c} and H_{3c}.

Because of the complex hierarchical nature of the model, we tested H_{2c} and H_{3c} using numerical simulation. Using the estimated parameters from the specified growth models, the range of the standardized scores of salesperson LO and PO in the data, and Aiken and West's (1991) recommendation in testing interaction, we replaced LO and PO with various values from –1 ("low", –1 standard deviation) to +1 ("high", +1 standard deviation) at Level 2 and then calculated the times at which the performance trajectories of salespeople with these goal orientation profiles reached the maxima and the corresponding maximum performance levels. Although the estimated times at which performance was maximized were roughly one month beyond the observation range (for the advantages of the HMLM's empirical Bayesian method to predict future status over ordinary least squares, see Raudenbush and Bryk 2002), simulation results in Table 3 clearly show that low-LO salespeople would level off at a maximum performance of .98, or 2% below the quota. Meanwhile, high-LO salespeople would level off at a higher maximum, 1.057, which would be approximately 6% above the quota. In contrast, low-PO salespeople would be 6% above their quota, while high-PO salespeople would be 2% short of quota. These results provide support for H_{2c} and H_{3c}. (Readers can also refer to time to minimum as a contrast.)

We plotted the interactions by computing the performance trajectories for "high," average (mean), and "low" levels of LO and PO. These plots parallel conventional

TABLE 3
Simulation of Performance Trajectories' Maxima and Minima

Trajectory Parameters	Learning Orientation Standardized Score										
	–1	–.8	–.6	–.4	–.2	0	.2	.4	.6	.8	1
t-min	5.75	5.40	5.12	4.89	4.70	4.54	4.40	4.28	4.18	4.09	4.01
Perf-min (1 = 100%)	.958	.959	.959	.959	.959	.959	.959	.958	.958	.957	.957
t-max	12.40	12.37	12.34	12.32	12.30	12.29	12.28	12.27	12.26	12.25	12.25)
Perf-max	.981	.988	.996	1.003	1.011	1.019	1.026	1.034	1.041	1.049	1.057
Trajectory Parameters	**Performance Orientation Standardized Score**										
	–1	–.8	–.6	–.4	–.2	0	.2	.4	.6	.8	1
t-min	4.13	4.19	4.26	4.34	4.43	4.54	4.67	4.83	5.02	5.27	5.61
Perf-min	.948	.950	.953	.955	.957	.959	.961	.963	.965	.966	.968
t-max	12.68	12.62	12.55	12.48	12.39	12.29	12.16	12.01	11.83	11.59	11.26
Perf-max	1.057	1.050	1.042	1.034	1.026	1.019	1.011	1.004	.996	.989	.982

Notes: t-min = time to minimum (month), t-max = time to maximum (month), Perf-min = minimum performance on sales quota, and Perf-max = maximum performance on sales quota. We used standardized scores for LO and PO; –1 = one standard deviation below the mean of zero (low condition), 1 = one standard deviation above the mean of zero (high condition), and 0 = average.

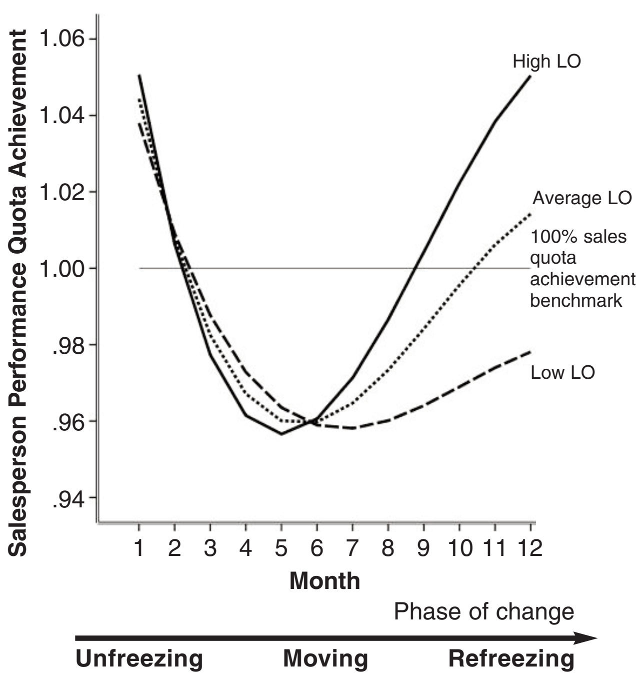
methods for depicting interactions following significant moderated multiple regression results. As Figure 2 shows, to the extent that salespeople reported relatively high LO, their performance suffered during the training periods leading to the actual rollout of the new technology. Presumably, such salespeople were diverting their attention from job activities to learning the new system. However, these same people evidenced the most positive slope following the rollout and exhibited the highest sales performance six months later. In contrast, while the performance of salespeople with relatively low LO suffered the smallest performance decrements through the training period, their performance continued to taper off and illustrated lower performance six months later. Presumably, this was attributable, at least in part, to them not having learned the intricacies of the new technology. This pattern of results is consistent with the form advanced in H_{2a}–H_{2c}.

Figure 3 shows the influence of salespeople's PO on their performance trajectories over time. This plot is virtually a mirror image of that for the LO influence, even though LO and PO were positively correlated ($\rho = .53$, $p < .001$) and both effects were modeled simultaneously. Specifically, to the extent that salespeople reported relatively high PO, their sales performance suffered the least during the training period. However, these high-PO salespeople evidenced a sharp decline in sales performance following the actual rollout. In contrast, the sales performance of people with relatively low PO declined the most during the training period and then evidenced the steepest positive slope following the intervention. These results are consistent with the trajectories advanced in H_{3a}–H_{3c}.

General Discussion

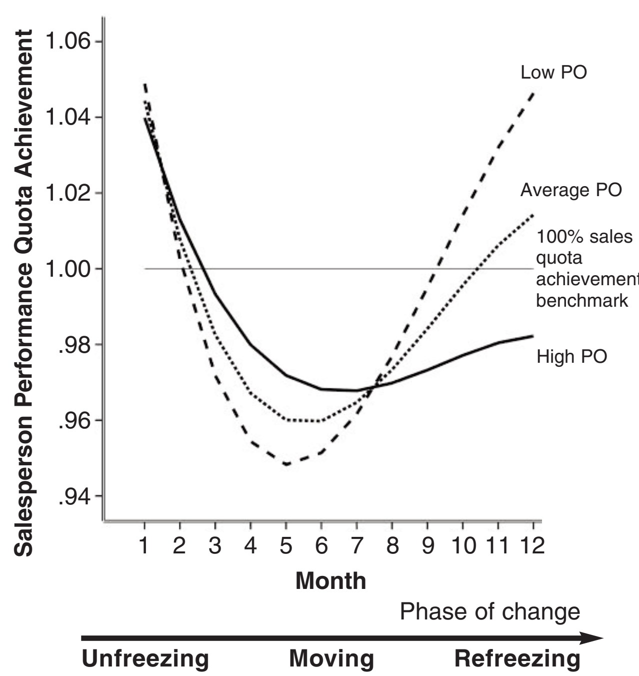
Scholars have illustrated that time can and should enter into theories to capture possible nonlinear relationships, to improve causal inference, and to reflect the reality that performance is time dependent (Chen and Mathieu 2008; Hofmann, Jacobs, and Baratta 1993; Rindfleisch et al. 2008). The criticality of time moves to the fore in the context of organizational change (Armenakis and Bedeian 1999; Van de Ven and Poole 1988). We add empirical support to these claims. This study not only examines the largely ignored dynamic relationship between salesperson goal orientations and performance but also opens up a new perspective on studying several important phenomena in the change-laden personal-selling profession. In addition, the findings provide a sneak peek into the fascinating role of human factors in CRM processes that deserve more academic attention (Boulding et al. 2005). The results also complement the literature on market-driven organizational learning and LO (Baker and Sinkula 1999; Calantone, Cavusgil, and Zhao 2002) in that learning, at either the individual or the organizational level, has an important influence on performance during times of turbulence. Next, we briefly discuss the findings, their implications, and opportunities for further research.

FIGURE 2
LO Longitudinal Influence on Salesperson Performance Trajectories



Notes: The figure was plotted using unstandardized estimates. A value of 1.00 on the vertical axis reflects 100% quota achievement.

FIGURE 3
PO Longitudinal Influence on Salesperson Performance Trajectories



Notes: The figure was plotted using unstandardized estimates. A value of 1.00 on the vertical axis reflects 100% quota achievement.

Consistent with the hypotheses based on the Lewin–Schein theory of change, the results suggest that surrounding an organizational change intervention, the average salesperson performance trajectory declined during the unfreezing phase, increased during the moving phase, and leveled off during the refreezing phase. We found that LO amplified the performance drop in the unfreezing phase, accelerated the positive recovery slope during the moving phase, and increased the level at which performance restabilized during the refreezing phase. In contrast, PO countervailed the effects of LO on salespeople's performance trajectory. The results seem to suggest that high-PO salespeople follow a more short-term-oriented strategy to adapt to change and are more likely to become slaves to routines than those with high LO.

By shifting the focus of research on salesperson performance in times of stability to times of change, we show that the relationship between salesperson traits and performance is nonlinear and more complex than a simple positive or negative relationship. The change of the sign of the relationship between individual traits and performance over time is important in several regards. First, it shows that while salespeople react to organizational change in different ways, it is possible to identify distinct patterns of their adaptation to the change, using predictors that are known to be stable over time. Second, mixed findings in previous research on the relationship between salesperson goal orientations and performance, ranging from a strong and positive relationship (Sujan, Weitz, and Kumar 1994) to no relationship (Kohli, Shervani, and Challagalla 1998), might be due to the failure to consider the criticality of time (Kohli, Shervani, and Challagalla 1998; Payne, Youngcourt, and Beaubien 2007; Rindfleisch et al. 2008). For example, the current findings seem to suggest that high-PO salespeople tend to invest time in shallow learning and therefore are less prone to performance decline during the unfreezing phase of a change; yet these same salespeople will have a difficult time recovering during the subsequent moving and refreezing phases. Had we narrowed our attention to the initial unfreezing stage only, we might have erroneously concluded that PO helped salespeople maintain good performance during times of change.

To make this concrete, Table 4 shows that had we used familiar techniques, such as multiple regression analysis, and confined ourselves to cross-sectional data for a specific month, we would have come to any of the following incomplete conclusions: (1) the relationship between goal orientations and performance does not exist, (2) LO is positively and/or not related to performance, and (3) PO is positively and/or not related to performance. In other words, a longitudinal research design can be useful in understanding the dynamics of salesperson performance during times of instability.

This study yielded some other noteworthy results. Though not hypothesized, it is intuitively possible that LO and PO interactively determine how a salesperson adapts to the change. The pairwise correlation between LO and PO in this study is positive and moderately high ($\rho = .527$, $p < .00$). This is consistent with previous research showing that these two traits are not on opposite sides of a continuum (e.g., Button, Mathieu, and Zajac 1996; Kohli, Shervani, and Challagalla 1998); thus, there is a possibility of an interaction. However, in our post hoc analysis, the interaction between these two traits in predicting salesperson performance trajectories was not significant. In conjunction with the effects we found, this buttresses the notion that these two traits not only operate independently but also countervail each other (i.e., one facilitating change, one impeding change). This reflects the paradox of stability and instability (Van de Ven and Poole 1988, p. 48).

How should the results be interpreted given the high positive pairwise correlation between LO and PO? First, this means that LO and PO have countervailing effects that call for managerial attention during change. Second, pairwise correlation is based on the assumption that the relationship between constructs is linear. As a side note, we ran a regression of LO on PO and its square term. We found that both the linear ($\beta = .43$, $p < .00$) and the quadratic ($\beta = –.25$, $p < .00$) terms were highly significant. This implies that the relationship between LO and PO might be nonlinear, following an inverted U shape. This also suggests that high-PO salespeople can be low-LO salespeople. The literature has been silent on this, and we refrain from making any hasty conclusion. Further research is needed to examine this issue.

Managerial Implications

How do managers identify determinants of salesperson adaptation to change? The results suggest that not all dispositions will determine how people adapt. For a learning-

TABLE 4
Cross-Sectional Multiple Regression Results

	Performance											
Predictors	**t = 0**	**t = 1**	**t = 2**	**t = 3**	**t = 4**	**t = 5**	**t = 6**	**t = 7**	**t = 8**	**t = 9**	**t = 10**	**t = 11**
OC	.03	.02	–.01	–.07	.06	–.02	.02	–.01	–.02	–.01	–.02	–.04
USE	.07	.12**	.05	.05	–.06	–.02	–.02	–.07	–.01	.03	.04	.07
EXP	–.06	.01	–.01	.06	.06	.06	–.03	–.03	–.00	.01	.00	.04
LO	.02	–.02	–.05	–.02	–.05	.02	.08	.11*	.07	.02	.04	.09
PO	–.02	.04	.08	.14**	.08	.06	–.04	–.05	–.07	–.05	–.02	–.08

*$p < .10$.
**$p < .05$.
Notes: OC = openness to change, USE = previous technology use, and EXP = experience. Cells depict standardized coefficients.

related change, we found that goal orientations are important while experience is not, and prior technology use plays only a minimal role. This suggests that a strong predictor of how people adapt to change should have a shared meaning with the nature of the change. It follows that managers should be aware that for other types of change that do not require extensive learning, variables, such as experience, adaptive selling, competiveness, or relationship characteristics, might move to the fore. We have yet to identify a comprehensive list of predictors of salesperson performance during change, but the notion of shared meaning should help guide managers.

What do managers do with an awareness of salesperson goal orientations? The results provide a clear implication for sales managers in terms of selection processes. Overall, salespeople with a relatively high LO, as well as those with relatively low PO, benefited from the introduction of the new CRM technology. Although in the short run such salespeople do not necessarily perform better, they will perform better than their counterparts in the long run when adapting to the change. However, managers do not always have the luxury of selecting people with ideal personality traits, so what can they do to facilitate both sales performance and implementation during the change process? We propose that the key lies in how the organization defines salespeople's performance. In this study, salespeople are rewarded for their sales relative to a quota. Although sales quotas are an appropriate and frequently used metric for sales performance during times of stability, managers should consider temporarily redefining performance metrics (and adjusting compensation) during a period of change to include change implementation behaviors (e.g., technology use in our context) in addition to sales. Such an adjustment would redirect high-PO employees' perceptions of what it means to perform, thus facilitating their ability to adapt. Managers pursuing this option should be careful to monitor their salespeople's adaptation to readjust the compensation plan at the optimal time.

Limitations and Further Research

This study is not free from limitations. We focus on only one type of planned change that, in the aggregate, exerted a long-term negative impact on sales and took place in a single firm. Although growth modeling is not new, we believe that other applications of growth modeling in sales and marketing management will produce important insights into several other change phenomena that are inherent in the sales force. For example, further research could apply similar models in other change contexts, including intended changes initiated by the focal firm (e.g., territory realignment, new product introduction, new market entry) and unintended changes brought on by external influences (e.g., market downturns, competitor's actions, a misconduct scandal, loss of a key account). In addition, the change in this study was preannounced; thus, the three phases of change are well defined and fairly gradual. It would be worthwhile to examine how unexpected, critical events influence the "punctuated equilibrium" (Gersick 1988) of work groups and individuals. Furthermore, regardless of whether the change is planned or unplanned, not all changes are disruptive in the sense that we have discussed. A different adaptation model would be expected for a change that is enhancing, such as when a primary competitor goes out of business and drives customers to the focal firm or when the company hires additional salespeople. These areas deserve additional research.

The study focuses on salespeople's goal orientations as a predictor of how they adapt to change. Although these higher-order dispositions are important, it might be useful to explore other predictors of adaptation and learning, such as organizational culture and market orientation (e.g., Baker and Sinkula 1999; Calantone, Cavusgil, and Zhao 2002), positive affect, attitude toward the change (Ye, Marinova, and Singh 2007), or time-varying goal orientation states. For example, further research might use field experiments to explore the impact of sales managers on salesperson adaptation to change by creating supplemental and complementary person–environment fit that are similar to Chen and Mathieu's (2008) work using students.

The results should be interpreted with the limitation that we did not have access to sales quota performance of the previous year. Although sales quotas already control for several important variables, such as seasonal fluctuations (Churchill et al. 1985; Zoltners, Sinha, and Lorimer 2006), the comparison of performance of the year of the change with that of the previous year may further solidify the findings. It may also be argued that the observed pattern was due to quota adjustment for low performers during the second phase of the change. Conceptually, if the adjustment had been fairly made to all underperformers, it could not have explained why low-LO and high-PO salespeople continued to be poor performers after the change. In addition, investigation of other dependent variables, such as sales call effort and intervening variables (e.g., time allocation between learning and selling; see Hunter and Perrault 2007), might be useful in explicating the underlying mechanism of the observed phenomenon.

We were able to track salesperson performance only six months after the intervention. Longer tracking might allow for deeper insights into the interaction between goal orientations and performance over time. This length of tracking, albeit contextually dependent, definitely deserves more research effort to explore. Finally, our adoption of the cubic function was instrumental in exploring the change phases, but we do not posit that all types of organizational change will follow this functional form. However, we hasten to add that the implications of organizational change on performance trajectories during the Lewin–Schein phases of change are important and deserve more empirical investigation. We also believe that caution is warranted insofar as extending temporal contiguity might introduce unwanted noise into the process that dampens causality inference (Rindfleisch et al. 2008).

Appendix

A Two-Level Model of Growth

Growth modeling using hierarchical multivariate linear models is an effective way to study individual change. Most individual change phenomena can be represented through a two-level hierarchical model (Raudenbush and Bryk 2002). The Level 1 regression captures within-subject growth trajectory that depends on a set of parameters. These individual growth parameters are then used as outcome variables in a Level 2 model. For this study, we specify the Level 1 model that captures individual salesperson performance during 12 months as a cubic function of time, $Y_{ti} = \pi_{0i} + \pi_{1i}t + \pi_{2i}t^2 + \pi_{3i}t^3 + e_{ti}$, where t is time and i represents the individual, and the Level 2 model treats each of the Level 1 parameters as a function of five predictors, which include three covariates (OC: openness to change, EXP: experience, and USE: previous use of technology) and two types of goal orientation (LO and PO).

$$\pi_{0i} = \beta_{00} + \beta_{01}(OC_i) + \beta_{02}(EXP_i) + \beta_{03}(USE_i) + \beta_{04}(LO_i) + \beta_{05}(PO_i) + r_{0i}.$$

$$\pi_{1i} = \beta_{10} + \beta_{11}(OC_i) + \beta_{12}(EXP_i) + \beta_{13}(USE_i) + \beta_{14}(LO_i) + \beta_{15}(PO_i) + r_{1i}.$$

$$\pi_{2i} = \beta_{20} + \beta_{21}(OC_i) + \beta_{22}(EXP_i) + \beta_{23}(USE_i) + \beta_{24}(LO_i) + \beta_{25}(PO_i) + r_{2i}.$$

$$\pi_{3i} = \beta_{30} + \beta_{31}(OC_i) + \beta_{32}(EXP_i) + \beta_{33}(USE_i) + \beta_{34}(LO_i) + \beta_{35}(PO_i) + r_{3i}.$$

Intuitively, when the Level 2 regressions are replaced into the Level 1 model, we have a series of interactions between time and the Level 2 predictors. Theoretically, these interaction terms capture the longitudinal effect of these between-subjects predictors on intraindividual growth trajectories (e.g., salesperson performance) over time.

Estimation Steps

Briefly, the estimation of these models involves the following steps: The estimation begins with an unconditional model, which is equivalent to a one-way analysis of variance model, to decompose the variance in the dependent variable into within-subject and between-subjects components. If between-subjects variances exist, the analysis moves to specifying a growth trajectory for Level 1 and treating the Level 1 parameters as fixed at Level 2. These constraints are subsequently relaxed to examine whether it is justifiable to treat these Level 1 parameters as random rather than fixed at Level 2. This step can also be conducted by first specifying these parameters as random at Level 2 to determine whether their Level 2 variances are significant. The tests of these nested models normally use a chi-square difference test of deviance scores (denoted $D = -2 \times$ log-likelihood). The Level 1 time scores are normally centered on a theoretically interesting point to facilitate interpretation. For this study, we clocked time such that the initiation of the planned change (i.e., the month when training began) was equivalent to $t = 0$.

The Level 1 error structure may follow various assumptions that can be empirically tested. The simplest is to assume that each e_{ti} is independently, identically, and normally distributed with a mean of zero and constant variance σ^2. For multiple repeated measures, researchers typically specify a first-order autoregressive model, heterogeneous Level 1 variance, or an unrestricted model and compare deviance scores to select the model that best fits the data and is most parsimonious. In the unrestricted model, there is a $T \times 1$ vector of errors following a common T-variate normal distribution with means of 0 and a general variance–covariance matrix, Σ (Raudenbush and Bryk 2002, p. 191). For this study, $T = 12$. The Level 2 random effects for individual i are assumed to be multivariate normally distributed with mean of 0. In unrestricted models, Level 2 random effects are integrated into the Level 1 error structure (Raudenbush et al. 2001) (for further details on growth models, see Raudenbush and Bryk 2002; Singer and Willett 2003).

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