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Unpacking the Relationship Between Sales Control and Salesperson Performance: A Regulatory Fit Perspective

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Abstract

The literature examining the effect of sales control on salesperson performance is, at best, equivocal. To reconcile inconsistencies in empirical findings, this research introduces two new types of salesperson learning: exploratory and exploitative learning. Drawing on regulatory focus theory, the authors conceptualize exploratory learning as promotion focused and exploitative learning as prevention focused and find that salespeople exhibit both exploratory and exploitative learning, though one is used more than the other depending on the type of sales control employed. The results also suggest that fit between salesperson learning and customer (i.e., purchase-decision-making complexity) and salesperson (i.e., preference for sales predictability) characteristics is critical to salesperson performance and that salesperson learning mediates the relationship between sales control and salesperson performance (Study 1). Study 2 corroborates the findings using new panel data collected over two waves. The results of this research have important implications for integrating sales control, salesperson learning, and salesperson performance.

Keywords: sales control, exploratory learning, exploitative learning, customer decision-making complexity, sales predictability, regulatory focus theory

An effective sales force is an indispensable asset, as salespeople play a fundamental role in marketing strategy implementation (Kumar, Sunder, and Leone 2014). A competent sales force is vital for firms attempting to outperform competitors through enhanced customer service and satisfaction. However, salespeople are some of the most costly resources to acquire, develop, and manage (Zoltners and Sinha 2005). According to a survey conducted by the Association for Talent Development, "U.S.-based companies spend approximately $20 billion per year on sales training. Yet, many sales organizations get low ROIs from their sales training initiatives" (Behar 2014). Not surprisingly, the literature has focused on sales control systems as a reflection of firms' efforts to productively utilize the knowledge, experiences, and skills of their salespeople; to motivate them to perform; and to help them maximize work outcomes (e.g., Ahearne et al. 2010).

As the sales job often involves independent, entrepreneurial, and autonomous tasks and responsibilities, building an effective sales control system is an important means to successfully manage salespeople. A sales control system is defined as "the organization's set of procedures for monitoring, directing, evaluating, and providing feedback to its employees" (Anderson and Oliver 1987, p. 76). It has been suggested that different types of sales control systems (e.g., outcomes, activities) can be conducive or restrictive to salesperson performance (e.g., Miao and Evans 2013; Oliver and Anderson 1994). However, the literature offers conflicting evidence (see Table 1), and therefore no clear guidelines, about the link between various types of sales control systems and salesperson performance (e.g., Challagalla and Shervani 1996).[1]

[Insert Table 1 here]

[1]A systematic review identifies two streams of research: one stream focuses on performance outcomes at the sales unit level (e.g., Cravens et al. 1993; Oliver and Anderson 1994), and the other investigates performance outcomes at the salesperson level (e.g., Challagalla and Shervani 1996; Miao and Evans 2013). The current study focuses on the individual salesperson and examines the effects of sales control systems on a salesperson's performance as evaluated by the sales manager, consistent with recent research (e.g., Evans et al. 2007; Miao and Evans 2013).

Sales scholars have raised concerns about the ability of sales control systems to have a direct effect on salesperson performance (e.g., Evans et al. 2007; Kohli, Shervani, and Challagalla 1998). The elusive and contentious notion of a direct relationship has been voiced in the literature, suggesting that direct effect results “either did not support or provided contradictory support for the hypotheses” (Lusch and Jaworski 1991, p. 412). While some studies find a positive link between outcome control and performance (e.g., Evans et al. 2007), others report no relationship (e.g., Kohli, Shervani, and Challagalla 1998; Miao and Evans 2013), and still others reveal a negative link (e.g., Fang, Evans, and Landry 2005). This study helps clarify the path from sales control to salesperson performance by offering new empirical evidence on the underlying mechanism and contingencies in this relationship.

In this paper, we apply the concepts of exploratory and exploitative learning from the organizational learning literature (e.g., Levinthal and March 1993; March 1991) to the salesperson context, which has received neither conceptual nor empirical attention in the extant literature. We define exploratory learning as a salesperson’s opportunity-seeking learning behavior that is based on entrepreneurial actions focused on experimenting with, searching for, and discovering novel, creative, and innovative selling techniques. We define exploitative learning as a salesperson’s advantage-seeking learning behavior that enhances productivity and efficiency by adhering to proven methods of selling and leveraging existing knowledge and experience, resulting in minimal deviation from routine selling (Tuncdogan, Van Den Bosch, and Volberda 2015). We ground these two types of learning in regulatory focus theory (RFT; see Higgins 1997, 2002) and propose that the two learning behaviors represent contrasting approaches to addressing customer problems. Specifically, exploratory learning is promotion focused and involves the renewal and reconfiguration of existing selling skills to develop novel solutions, while exploitative learning is prevention focused and involves the adherence to current selling skills and practices that play to the salesperson's strengths, thus resulting in a safer, more established, and proven approach (Tuncdogan, Van Den Bosch, and Volberda 2015).

In developing our conceptual model, we draw on RFT (Higgins 1997, 2002) and regulatory fit to (1) investigate how salespeople adopt the two learning behaviors to varying degrees in response to different types of control systems, (2) examine the indirect effect of controls on salesperson performance as mediated by exploratory and exploitative learning, and (c) explore how these learning behaviors differentially affect salesperson performance under the conditioning roles of salesperson and customer characteristics. We test the conceptual model using primary data from salespeople and their supervisors within pharmaceutical firms.

The pharmaceutical sector is undergoing a sweeping transformation, as the critical decision makers about drugs are changing from doctors to hospital administrators. The shift in the decision-making unit from a doctor to a team of administrators and doctors (Bonoma 2006) makes the sales of pharmaceutical products much more complex and thus offers a fertile context in which to test our model. The sales function in the pharmaceutical industry is based on effectively managing the requirements of unique customer groups: (1) physicians, the most important customer segment because they have the authority and expertise to make decisions about prescribing a drug; (2) hospitals, which are high-volume customers that buy directly from pharmaceutical companies and wholesale drug distributors; and (3) patients, who use and buy the medicines (though physicians must still decide on the selection of drugs). Doctors, who are charged with caring for their patients, prescribe certain drugs (vs. other drugs) for their healing attributes, but they must do so within constraints set by insurance companies and governmental regulations.

The sales function within pharmaceutical companies is typically organized as different units that are constructed to meet the particular requirements of diverse market segments and individual customers (e.g., diabetes consultants, hospitals). Sales reps focus their attention on developing and managing close relationships with doctors, who are often confronted with better-informed and more demanding patients, growing health cost pressures, and limited time to meet and interact with medical reps (e.g., Ahearne et al. 2010; Kappe and Stremersch 2016).

Our study contributes to the literature in three important ways. First, we integrate the sales control and learning literature and show that different sales control systems influence distinct salesperson learning approaches in different ways. Thus, consistent with RFT, we conceptualize exploratory and exploitative learning as malleable states (i.e., situationally induced) in response to different types of sales controls, not as stable and fixed traits or dispositions (Higgins 2002).

Second, this study helps reconcile discordant findings on the link between sales controls and performance. At the core of this unresolved issue lies the theoretical and practical dilemma that companies experience when using sales controls. Firms often deploy controls in an effort to change a salesperson's behavior, ultimately hoping to improve his or her performance. Although cognitive and attitudinal change can lead to performance change, without change in action, the change may be modest or short lived at best. Thus, to address these mixed results, we use a dual mediating mechanism of exploratory and exploitative learning to show that different controls affect salesperson performance via increasing or decreasing the two learning behaviors. Prior research has attempted to show the performance impact of sales control indirectly through changes in cognition (e.g., psychological climate) (Evans et al. 2007) and job engagement (e.g., adaptive selling, sales effort), but these efforts have had limited success (Miao and Evans 2013). Our findings reveal that, rather than changes in cognition or attitude, behavioral change (i.e., salesperson learning) effectively mediates the relationship between sales control and performance.

Third, we contribute to the sales literature by articulating the conditions under which the strength of the salesperson learning–performance link varies. We introduce a salesperson characteristic (i.e., preference for sales predictability) and a customer characteristic (i.e., purchase-decision-making complexity) as moderators that have received limited attention despite their theoretical and practical relevance. These factors reflect the changing landscape of how purchase decisions are made in the pharmaceutical context. Preference for sales predictability is a dispositional concept that constitutes a key element of the sales task in this setting; specifically, it captures a salesperson's desire to convince doctors of a drug's efficacy and superiority in the hope of boosting prescriptions and closing sales transactions. Customers' purchase-decision-making complexity refers to the time, amount of information, and number of parties involved in a purchase decision. Because decision making about health care products is increasingly shifting from a single source (i.e., a doctor) to strategic procurement teams that include administrators and doctors (Rockoff 2014), it is important to consider purchase-decision-making complexity to delineate boundary conditions of the performance impact of salesperson learning.

We test our model across two studies and conclude with a discussion of the theoretical implications for integrating the sales control, salesperson learning, and salesperson performance literature streams. We offer practical suggestions for effectively aligning control systems with learning and leveraging learning according to salesperson and customer characteristics.

Theoretical Background

Model Overview

We ground our conceptual model (see Figure 1) in the overarching theoretical framework of RFT and argue that salespeople engage in exploratory and exploitative learning to different degrees depending on the type of sales control system deployed. We adopt a tripartite conceptualization of sales control (i.e., outcome, activity, and capability), consistent with the works of Challagalla and Shervani (1996) and Kohli, Shervani, and Challagalla (1998). In an attempt to reconcile conflicting findings in the literature on the sales control–performance link, our conceptual model posits that exploratory and exploitative learning are mediators. Consistent with regulatory fit, we also argue that performance will improve when salesperson learning "fits" with the preference for sales predictability and purchase-decision-making complexity.

[Insert Figure 1 here]

Salesperson Exploratory and Exploitative Learning

Exploratory learning refers to the "pursuit of new knowledge" (Levinthal and March 1993, p. 105) and is characterized by "search, variation, risk taking, experimentation, play, flexibility, discovery, and innovation" (March 1991, p. 71). Exploitative learning involves "the use and development of things already known" (Levinthal and March 1993, p. 105) and is characterized by "refinement, choice, production, efficiency, selection, implementation, and execution" (March 1991, p. 71).

We build on this strong theoretical foundation and propose that salesperson exploratory learning is a self-regulated promotion-focused behavior that involves searching for, experimenting with, and discovering new selling techniques and skill sets that help improve sales performance. In contrast, exploitative learning is a self-regulated prevention-focused behavior in which the salesperson adheres to proven existing selling techniques and skill sets that leverage known knowledge and capabilities to enhance performance. Regardless of which learning style a salesperson adopts, consistent with the RFT explanation of goal pursuit, both strategies strive to achieve the common goal of improved performance.

In marketing, exploratory and exploitative learning has been studied primarily at the firm level in the contexts of innovation (e.g., Atuahene-Gima 2005; Atuahene-Gima and Murray 2007; Jin, Zhou, and Wang 2016) and strategy (e.g., Kyriakopoulos and Moorman 2004; Vorhies, Orr, and Bush 2011). However, it is important to distinguish learning at different units of analysis because exploratory learning at the individual level may be considered exploitative learning at the firm level. Consider, for example, the case in which a salesperson experiments and discovers a new and unconventional approach to selling products, but then the sales organization capitalizes on this opportunity by exploiting it for scalability. What one salesperson may consider exploratory learning, another may perceive as exploitative learning, and vice versa. Thus, at the individual level, there can be considerable variation in terms of how people view what constitutes exploratory and exploitative learning.

The literature on organizational learning as a mediator between different types of strategic orientation and firm performance is inconclusive. For example, Noble, Sinha, and Kumar (2002) find that exploitative learning mediates the relationship between competitor orientation and return on assets. Atuahene-Gima (2005) shows that competence exploration fully mediates the effect of competitor orientation (but not customer orientation) on radical innovation performance, while competence exploitation partially mediates the effects of customer and competitor orientations on incremental innovation performance. Notwithstanding the contribution that organizational learning has made to the marketing literature, there is a dearth of research on exploratory and exploitative learning at the individual level (see Table 2), as echoed by Gupta, Smith, and Shalley (2006, p. 703), who note that “studies that examine exploration and exploitation at a micro level are relatively scarce.”

[Insert Table 2 here]

The few studies that have investigated salesperson learning tend to focus specifically on learning effort (Wang and Netemeyer 2002) and its link to organizational learning (Bell, Menguc, and Widing 2010). Yet two important issues merit further refinement and development. First, salesperson learning lacks a more nuanced articulation of the exploratory and exploitative learning approaches that salespeople pursue. Such learning occurs not only by acquiring new sales skills and techniques but also by refining, tweaking, and perfecting existing sales techniques to improve efficiency.

In the pharmaceutical context, for example, medical reps sell products to doctors and hospitals on the basis of information about drug efficacy, dosing, and side effects; drug and food interactions; and drug costs (see Kappe and Stremersch 2016). They search for novel ideas, skills, and knowledge and seek new selling techniques to promote drugs and build close relationships with customers (e.g., physicians, hospitals). For example, sales reps may research the hobbies and interests of a given doctor (e.g., wine, art, sports such as golf, travel, gastronomy) so that they can engage in an intellectual and personal conversation that goes beyond the mere recitation of drug facts. This approach describes exploratory learning. That said, given the complexity involved in health care product sales and the myriad constraints that doctors face, medical reps also need to deploy selling techniques that have proven to work well for them, reliable tactics that help them perform tasks productively and manage customer relationships efficiently. An example of such exploitative learning would be when a sales rep relies on predefined scripts that compare the pros and cons of their drug to those of competitors (i.e., strictly a product-centered approach). To provide some additional deeper context to these different approaches to learning, we conducted interviews with pharmaceutical sales reps to provide a better understanding and more specific examples of exploratory and exploitative learning (see Web Appendix A).

Second, the operationalization of salesperson learning suffers from an overlap with learning orientation. The items that comprise the individual learning effort dimension of salesperson learning in Bell, Menguc, and Widing (2010) mirror those of the learning orientation construct (Kohli, Shervani, and Challagalla 1998). Thus, there is a need to refine a more nuanced salesperson learning construct that is distinct from learning goal orientation and embodies learning through exploration and exploitation.

Finally, it is important that we distinguish the two learning approaches from learning orientation (also known as mastery orientation), which pertains to the intrinsic desire to learn and improve (Ames and Archer 1988). As Kohli, Shervani, and Challagalla (1998, p. 263) assert, "Salespeople with a learning orientation have a strong desire to improve and master their selling skills and abilities continually and view achievement situations as opportunities to improve their competence." In this study, we focus on salesperson exploratory and exploitative learning, but not on learning orientation, which we include as a control in our model (see Figure 1).

Regulatory Focus Theory (RFT)

RFT proposes two types of regulatory focus: (1) chronic regulatory focus describes a trait or disposition that is chronic and stable in nature, while (2) situational regulatory focus, which we adopt in this paper, is evoked and malleable and is affected by leadership style, organizational climate, and certain situational tasks and demands. Because of these characteristics of situational regulatory focus, it is typically hypothesized to be a mediator in many conceptual models (e.g., Neubert et al. 2008; Wallace and Chen 2006).

RFT explains how goals are achieved using two self-regulatory behaviors: promotion-focused and prevention-focused behaviors (Higgins 1997). Regulatory fit occurs when people pursue promotion- or prevention-focused strategies that are appropriately aligned with their regulatory orientation, with the task, or with situational demands (Higgins 2000). Regulatory fit suggests that people are more likely to achieve goals and perform better because fit increases motivation and engagement (Avnet and Higgins 2006). As Higgins (2000, p. 1219) notes, "people experience a regulatory fit when they use goal pursuit means that fit their regulatory orientations, and this regulatory fit increases the value of what they are doing."

Drawing on the situational (vs. chronic) perspective of regulatory focus, we define exploratory learning as opportunity seeking, entrepreneurial, innovative, experimental, and risk taking, and we categorize this type of learning as promotion focused (Liberman et al. 1999). Because exploratory learning is concerned with growth, the focal issue tends to be avoiding errors of omission (i.e., missing an opportunity that can lead to growth), resulting in a greater motivation to push boundaries and try new selling techniques (DeCarlo and Lam 2016). In contrast, exploitative learning, when viewed as advantage seeking, attempts to avoid deviations from proven tactics and enhance protection; as such, the primary motivation is to avoid errors of commission (i.e., making mistakes). Drawing on the situational perspective of regulatory focus, we categorize this type of learning as prevention focused because prevention-focused people prefer stability and show a strong endowment effect (Liberman et al. 1999).[2]

Hypotheses Development

[2]We substantiated our theoretical framework by collecting data in a pilot study of 78 salespeople in a midsized pharmaceutical firm. We measured promotion focus and prevention focus with a six-item, five-point (1 = "never," and 5 = "constantly") scale (Wallace and Chen 2006). We used the scales of exploratory and exploitative learning developed specifically for this study (see the "Instruments and Measures" section in Study 1). The model estimating exploratory (exploitative) learning as a function of promotion (prevention) focus suggests that (1) promotion focus is related positively to exploratory learning ($b = .285$, $p < .05$) but not to exploitative learning ($b = .085$, not significant [n.s.]) and (2) prevention focus is related positively to exploitative learning ($b = .309$, $p < .01$) but not to explorative learning ($b = –.174$, n.s.). These findings support our argument that promotion-focused salespeople tend to engage in more exploratory learning, while prevention-focused salespeople adopt exploitative learning. These results are consistent with Tuncdogan, Van Den Bosch, and Volberda's (2015) predictions that a promotion (prevention) focus is more strongly related to exploration (exploitation) than a prevention (promotion) focus.

Main Effects

Consistent with the tenets of regulatory fit, Wallace and Chen (2006, p. 533) argue that "different situations require different strategies, and, thus, a different regulatory focus. Hence, employees' levels of work-specific promotion focus and prevention focus may be more likely to change as situational stimuli change, such as when employees are exposed to changes in leadership, work climate, or task demands." The authors further maintain (p. 533) that "the choice for engaging in promotion or prevention strategies may depend at least in part on situational and task demands (Brockner and Higgins 1997)." Our preceding arguments are further justified by Anderson and Oliver (1987, p. 86), who state that "a salesperson's selling strategies also should be a function of the type of control system." Here, we focus on three primary types of control systems: outcome control, activity control, and capability control. We discuss each in turn in the following subsections.

Outcome control and exploratory and exploitative learning. The focus of outcome control is to monitor, evaluate, and provide feedback on a salesperson's results, including sales volume, sales revenue, and quota achievement (Kohli, Shervani, and Challagalla 1998). Outcome control underscores short-term results (Oliver and Anderson 1994). Salespeople are not rewarded for learning new sales techniques and approaches, but instead are compensated for attaining objective and quantifiable results. Thus, there is little motivation for salespeople to learn novel skill sets that might be risky, uncertain, and difficult to master quickly. Because salespeople are often compensated to some extent with monetary incentives as opposed to a more traditional set salary, time and effort invested in learning, experimenting with, and discovering creative and innovative selling techniques entail risk and ambiguity and can jeopardize their income.

It follows, then, that under outcome control, salespeople will adhere to proven and wellrehearsed selling techniques that are closely aligned with and reinforce their existing strengths and experience. Such salespeople tend to focus on preventing mistakes and minimizing variation in outcomes by refining their existing sales approaches to realize greater efficiency and productivity. As Oliver and Anderson (1994, p. 56) note, “outcome-control salespeople view time to train and learn as time out of the field (with a high opportunity cost) and are relatively unwilling to experiment with new products and approaches because their reliance on commission income pressures them to gain quick results.” Thus, we predict that outcome control encourages exploitative learning, which is prevention focused, and discourages exploratory learning, which is promotion focused. Formally,

> H_1: Outcome control results in (a) less exploratory learning and (b) more exploitative learning.

Activity control and exploratory and exploitative learning. The purpose of activity control is to monitor and evaluate salespeople on the basis of certain processes and activities and reward them for how well they follow a prescribed formula (Anderson and Oliver 1987). Activity control entails following day-to-day rules and procedures and complying with expectations. Empirical evidence (Oliver and Anderson 1994) suggests that activity control is most effective when salespeople are risk averse. Supervisors monitor activities that are mechanical and routine and do not deviate from standard practice (Kohli, Shervani, and Challagalla 1998).

Consistent with regulatory fit, salespeople engage in behaviors that are in line with the work environment or situation (Neubert et al. 2008; Wallace and Chen 2006). Because activity control emphasizes prevention-focused behavior via non-risk-seeking, routine, mechanical, and standardized activities (e.g., number of sales calls made, number of samples distributed), salespeople are likely to engage in more exploitative and less exploratory learning because it is a safer and more standardized type of learning and is a better overall fit with this type of working environment (Avnet and Higgins 2006).

H_2: More activity control results in (a) less exploratory learning and (b) more exploitative learning.

Capability control and exploratory and exploitative learning. The purpose of capability control is to develop salespeople's competencies so that they can perform better in their tasks and responsibilities. Capability control involves setting goals to develop sales techniques and customer relationship management abilities, monitoring and evaluating how salespeople are performing in relation to these goals, and providing feedback on areas that need improvement. By its nature, developing capabilities (e.g., the ability to close a sale without pressuring customers, managing customers' expectations and emotions) takes time and patience. Capabilities are typically tacit and thus require a long-term perspective to learn, develop, and master.

In the context of pharmaceutical sales, capability control is used to educate and train salespeople to understand the unique needs of doctors and hospitals so that they can tailor their sales pitch to different recipients. Role playing and contingency scenarios are developed so that salespeople can make the most out of their short meeting time with doctors. Capability control pushes salespeople to go beyond what the firm provides them with in terms of knowledge and resources and to use their individual strengths to connect and build rapport with doctors either through technical knowledge or personal affinity. Capability control also encourages salespeople to educate themselves so that they take risks and move beyond their comfort zones to experiment with bold and novel approaches to selling (e.g., talking about wine, arts, sports, or other hospitals' best practices)—whatever it takes to forge a connection with doctors.

When it is understood that supervisors are interested in investing in and evaluating their salespeople's capabilities, the message is that salespeople should be directing their behaviors more toward searching for and experimenting with innovative sales techniques rather than seeking to refine status quo approaches. Mistakes, deviations from routine selling, and trial and error are inevitable consequences of capability control, and such miscues are often viewed as the natural consequences of progression toward discovering novel solutions to customers' problems. Thus, capability control encourages exploratory learning that is promotion focused.

H_3: Capability control results in (a) more exploratory learning and (b) less exploitative learning.

The Mediating Role of Salesperson Learning

The discordant findings regarding the effects of sales control on performance prompted us to examine the complexity underpinning this relationship and, in turn, to propose a set of mediation hypotheses in an attempt to unpack this contentious issue. We reason that sales control is too distal to have a direct impact on performance and instead propose a new mechanism—namely, sales control influences performance through a more proximal path of salesperson learning. Specifically, we argue that sales control will enhance performance when salespeople self-regulate their behaviors (in either a prevention- or a promotion-focused manner) in ways that display regulatory fit with the type of control being used.

Using a distal–proximal framework, Lanaj, Chang, and Johnson (2012) show through meta-analysis that distal personality traits have an impact on work behaviors (e.g., task performance, organizational citizenship behavior, innovative performance) through more proximal regulatory focus. As the authors argue (p. 999), "because regulatory foci represent proximal motivational constructs (Scholer and Higgins 2008), they may operate as channels through which more distal individual differences affect work behaviors." Research has shown that regulatory-focused behaviors function as mediators between distal personal and situational antecedents and performance. For example, Wallace and Chen (2006) show that promotion and prevention regulatory foci mediate the relationships between conscientiousness and group safety climate and between production and safety performance. Research has also reported that prevention focus mediates the relationship of initiating structure with in-role performance and deviant behavior, while promotion focus mediates the relationship of servant leadership with helping and creative behavior (Neubert et al. 2008).

Given the strong theoretical and empirical support of the mediating role of regulatory foci, we posit that the two types of salesperson learning mediate the relationship between sales control and performance. However, because each type of sales control affects exploratory and exploitative learning in different directions, we expect different signs for the indirect effect depending on the relationship between sales control and learning.

For outcome and activity control, we predict that there will be a negative (positive) indirect effect on salesperson performance when mediated by exploratory (exploitative) learning. This reasoning is based on our prediction that outcome and activity controls discourage (encourage) exploratory (exploitative) learning. For capability control, we posit that there will be a positive (negative) indirect effect on salesperson performance when it is mediated by exploratory (exploitative) learning because capability control encourages (discourages) exploratory (exploitative) learning. The positive performance effects of exploratory and exploitative learning are in line with RFT; irrespective of whether a promotion- or prevention-focused behavior is used, both share the goal of improving performance. Formally, we propose the following hypotheses:

H_{4a}: Outcome control has a negative indirect effect on salesperson performance when it is mediated by exploratory learning.
H_{4b}: Outcome control has a positive indirect effect on salesperson performance when it is mediated by exploitative learning.
H_{5a}: Activity control has a negative indirect effect on salesperson performance when it is mediated by exploratory learning.
H_{5b}: Activity control has a positive indirect effect on salesperson performance when it is mediated by exploitative learning.

H_{6a}: Capability control has a positive indirect effect on salesperson performance when it is mediated by exploratory learning.

H_{6b}: Capability control has a negative indirect effect on salesperson performance when it is mediated by exploitative learning.

The Moderating Influences of Salesperson and Customer Characteristics

We chose the two moderators of (1) preference for sales predictability and (2) customers' purchase-decision-making complexity based on theoretical grounds that either can strengthen or weaken regulatory fit and ultimately influence performance by accentuating or attenuating the impact of regulatory-focused behavior on performance. On a practical level, it is also well known that salespeople are conscious of the need to close sales transactions and feel the pressure to do so. However, there is little academic research on this topic. Therefore, the construct of preference for sales predictability taps into this characteristic of a salesperson, and our model captures this construct as a moderator. Furthermore, given the pharmaceutical context of this study, it is appropriate to examine customers' purchase-decision-making complexity as a moderator because the number of parties involved in making purchase decisions about drugs is changing from a single source (e.g., doctors) to multiple parties (e.g., doctors and hospital administrators), and we expect such complexities to condition the impact of the two learning behaviors on performance (Bonoma 2006).

Preference for sales predictability. The literature on need for closure suggests that salespeople who have a high preference for predictability desire prompt, firm, and transparent answers (Webster and Kruglanski 1994). They are less tolerant of uncertainty and thus tend to avoid situations that are unpredictable and less straightforward. Therefore, salespeople with a high preference for sales predictability will prefer prevention-focused behaviors (Cesario, Grant, and Higgins 2004). The combination of exploitative learning and a high preference for sales predictability is compatible because both evoke a prevention focus, thus strengthening regulatory fit and, in turn, increasing performance. Conversely, the combination of exploratory learning and a high preference for sales predictability is incompatible because exploratory learning is associated with promotion-focused behavior, thus weakening regulatory fit and, in turn, mitigating performance. Thus, we propose the following:

> H_{7a}: The effect of exploitative learning on salesperson performance increases as a salesperson's preference for sales predictability increases.
> H_{7b}: The effect of exploratory learning on salesperson performance decreases as a salesperson's preference for sales predictability increases.

Customers' purchase-decision-making complexity. Purchase decision making becomes more complex when customers (1) take longer to make a purchase decision, (2) require more information to arrive at a purchase decision, (3) involve multiple parties rather than a single person, and (4) perform a purchase task that is new rather than routine or standard (e.g., Schmitz and Ganesan 2014). Therefore, high customer purchase-decision-making complexity creates a risky and uncertain situation in which prevention-focused behaviors are more likely to pay off and promotion-focused behaviors can be costly. Consistent with Jaworski's (1988) argument that fit between sales control and the environment is critical to realize performance, we posit that the impact of exploitative learning on salesperson performance will be elevated under high customer purchase-decision-making complexity.

As March (1991, p. 85) argues, "the distance in time and space between the locus of learning and the locus for the realization of returns is generally greater in the case of exploration than in the case of exploitation, as is the uncertainty." Therefore, the performance of a salesperson who relies on exploratory learning will suffer when dealing with customers whose purchase decision making accentuates, compounds, and acutely raises the risks associated with exploratory learning. This suggests that there is poor regulatory fit when a promotion-focused behavior such as exploratory learning is used in a situation that demands prevention-focused actions, as in high customer purchase-decision-making complexity. The overall effect, therefore, is to weaken the impact of exploratory learning on salesperson performance. Formally, we hypothesize the following:

H_{8a}: The effect of exploitative learning on salesperson performance increases as customer purchase decision making becomes more complex.
H_{8b}: The effect of exploratory learning on salesperson performance decreases as customer purchase decision making becomes more complex.

Research Approach

We tested our conceptual model across two studies using data collected from South Korea, one of the largest pharmaceutical markets in the world and the third largest in Asia, with sales expected to grow from $15.1 billion in 2015 to $18.3 billion by 2020. There is considerable government regulation on pricing and advertising to patients in the Korean pharmaceutical industry. All selling, marketing, and advertising activities are targeted toward physicians and hospital administrators rather than patients. The Korean pharmaceutical industry has one of the highest selling, general, and administrative expenses, which account for 30.5% of total sales, higher than the average 20% typically found in Korean manufacturing firms (Kim 2017). Therefore, the Korean pharmaceutical market can be characterized as an industry that competes mostly through sales promotion versus price differentiation. Doctors occupy an important position (although the decision-making unit becomes more complex for larger university hospitals) in deciding which prescription drugs to use. This implies that salespeople have a window of opportunity in influencing a doctor to use their drugs. Thus, the pressure to be creative and leave a lasting impression and to stand out from the crowd is key to influencing doctors to choose their drugs.

Furthermore, the Korean government regulates rebates (i.e., gifts and monetary incentives) and kickbacks that pharmaceutical firms use to persuade doctors to prescribe their drugs, although such practices have yet to be firmly rooted out. Such an environment pushes salespeople to experiment with new selling techniques and forces them to step outside of their comfort zones. For example, they understand that they must try to learn foreign selling approaches, which may not necessarily play to their strengths. Thus, the competency of sales representatives is a critical asset that can determine the fate of pharmaceutical firms in this industry. The two companies chosen for this study are global pharmaceutical companies operating in South Korea. The first company markets more than 80 products and has annual sales exceeding $300 million, while the second firm sells more than 100 products and has sales exceeding $350 million.

In Study 1, we collected salesperson data on control systems (Wave 1) and, after two months, data on salesperson learning and customer and salesperson characteristics (Wave 2). Then, we matched salesperson data with sales managers' evaluations of salesperson performance, which we gathered three weeks after Wave 2. However, the model does not fully capture the change in salesperson learning and performance over time. Thus, in line with recent research (Kumar et al. 2011; Kumar and Pansari 2016), we conducted Study 2 to assess the robustness of our model using panel data collected from salespeople and sales managers at two points in time. There is a dearth of studies that offer insights into how salesperson learning unfolds over time (Mathieu et al. 2008), and our two studies are designed to fill this gap.

Study 1

Instruments and Measures

We designed our study and took all necessary procedural measures to minimize common method bias (Podsakoff et al. 2003). To reduce evaluation apprehension and protect anonymity, respondents were assured that there were no right or wrong answers and that responses would remain strictly confidential. We randomized the order of the measures to reduce respondents' tendency to rate items similarly (e.g., rating control systems and exploratory and exploitative learning consistently high or low). To limit potential common method bias effects, we obtained data on salesperson performance from sales managers and data on all other constructs from salespeople at two points in time. Because the unit of analysis is the individual salesperson, we measured all variables at the individual level. Unless otherwise stated, we used a five-point scale to assess responses (see Table 3).

[Insert Table 3 here]

Exploratory and exploitative learning. Because there are no established scales that measure exploratory and exploitative learning in the sales context, we developed the scales according to the following steps[3] (Churchill 1979). First, we generated items to tap exploratory and exploitative learning. Following existing firm- and/or unit-level scales (e.g., Atuahene-Gima and Murray 2007), we used buzzwords such as “explore,” “search,” “discovery,” “experimentation,” “risk taking,” and “novelty” for exploratory learning and “implementation,” “proven approaches,” “adherence,” “efficiency,” and “productivity” for exploitative learning (March 1991, p. 71). We were careful to put together scale items in such a way as to create two distinct measures of learning so that they would not overlap with existing measures, such as adaptive selling. Second, we conducted in-depth interviews with 20 salespeople, instructing them to assess the scale items in terms of relevance, clarity, and thoroughness. We made necessary revisions in line with their feedback. Third, we assessed the revised scales using data collected from a new batch of 78 salespeople. Test results indicated that the scales were reliable, valid, and unidimensional, so it was not necessary to drop any scale items to improve reliability or validity.

Control systems. We measured activity control (five items) and capability control (five items) with scales borrowed from Kohli, Shervani, and Challagalla (1998). We operationalized

[3] In-depth interviews with managers and sales representatives clearly indicated salespeople’s involvement in exploratory and exploitative learning in an effort to improve their sales tasks.

outcome control in terms of incentive rate using Lo, Ghosh, and LaFontaine's (2011) formula. Specifically, we calculated incentive rate for each salesperson as the ratio of total variable compensation (i.e., total compensation minus base salary) to sales revenue in the last financial year. We chose this measure over alternatives (e.g., variable-to-total compensation) because it is "consistent with the notion of ex ante incentives per agency theoretic models and thus is not susceptible to distortions arising from ex post realizations of outcomes" (Lo, Ghosh, and LaFontaine 2011, p. 788).

Moderating variables. We measured preference for sales predictability using a four-item scale.[4] Preference for predictability is one of the dimensions of Webster and Kruglanski's (1994) higher-order need-for-closure scale, which has been adapted to various contexts such as consumer information search and shopping behavior (e.g., Choi et al. 2008; Houghton and Grewal 2000). We adapted previously validated items to the sales context. We measured customer purchase-decision-making complexity using a five-item scale (John and Weitz 1989).

Salesperson performance. We asked sales managers to rate the extent to which salespeople met sales objectives. We measured salesperson performance with a seven-item formative scale (1 = "needs improvement," and 5 = "outstanding") (Behrman and Perreault 1982).

Control variables. We detail the control variables in Web Appendix B.

Sample and Data Collection

We used a two-wave, multirespondent approach to collect data from two large pharmaceutical firms with the endorsement of their human resources managers.[5] We collected the salesperson

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[4]Our scale differs from Lo, Ghosh, and LaFontaine's (2011) salesperson risk aversion scale. These authors measure "the manager's perceptions of the focal salesperson's preference for income stability and aversion to variations in outcomes and pay" (p. 789), whereas our measure captures a salespeople's perceptions of preference for predictability in sales situations and aversion to variations in customers' expectations.

[5]We dummy-coded the two firms to control for their fixed effects on learning and performance using the weighted dummy variable approach (Aiken and West 1991) due to an unequal distribution of responses from each company.

data in two waves. In the first wave, we sent the questionnaire to 616 salespeople via a link in the firms' intranet system. Salespeople were informed about the purpose of the study and the confidentiality of responses and they were asked to respond to questions about demographics, learning goal orientation, sales volatility, activity control, and capability control. After two reminders, we obtained 414 usable salesperson responses. Two months later, we conducted the second wave of the study with the initial 414 responding salespeople, who were then asked to respond to questions pertaining to exploratory and exploitative learning, preference for sales predictability, and customers' purchase-decision-making complexity. After two reminders, we received 378 usable responses (Company A = 142; Company B = 236), for a response rate of 61% (Company A = 61%, Company B = 64%).

Three weeks later, we collected data from sales managers. We received responses from 42 managers, who, on average, provided information on the performance of nine salespeople. We found no significant differences between early and late respondents with regard to the model constructs, demographics, and matched performance data. Salespeople were mostly male (91.5%), were an average of 34.9 years of age, served an average of 62 customers, and received an average of 40.6 hours of training. In addition, 54% held graduate degrees, and they averaged 7.4 years of territory experience, 4.8 years of firm experience, and 7.4 years of career experience.

Measure Validation and Common Method Bias

Measure validation. We conducted a confirmatory factor analysis (CFA) to assess the reliability and validity of the measures to which salespeople had responded. The CFA shows good fit to the data, after we deleted items with a low factor loading (see Table 4). The composite reliability and average variance extracted values were above .70 and .50, respectively. Standard testing procedures (Anderson and Gerbing 1988; Bagozzi and Yi 1988; Fornell and Larcker 1981) supported both convergent and discriminant validity of the measures (Table 5).[6]

[Insert Tables 4 and 5 here]

Common method bias. We assessed the extent of common method bias in salesperson-rated measures using the marker variable technique (Lindell and Whitney 2001). A three-item scale of firm dependence on the key supplier (Jap and Ganesan 2000) served as a marker variable because it is not theoretically related to the study's core variables and has good reliability (M = 3.47, SD = .82, Cronbach's α = .78). Common method bias was not a major threat, as the pattern and magnitude of covariances did not change significantly before and after the marker variable's inclusion in the measurement model.

Model Estimation

We estimate the model by taking into consideration (1) measurement error, (2) alternative models, and (3) endogeneity of exploratory and exploitative learning. We review each of these in Web Appendix C.

Results

Main effects. As Table 6 reports, outcome control is negatively related to exploratory learning ($b = -.072$, $p < .01$) and positively related to exploitative learning ($b = .107$, $p < .01$), in support of H_{1a} and H_{1b}. Activity control is not related to exploratory learning ($b = .020$, not significant [n.s.]) but is positively related to exploitative learning ($b = .257$, $p < .01$), in support of

[6]The exploratory and exploitative learning measures must also be distinct from those of related constructs, such as adaptive selling (Spiro and Weitz 1990) and learning goal orientation (Sujan, Weitz, and Kumar 1994). We compared the unconstrained and constrained (i.e., the correlation between constructs was set to 1) models (Anderson and Gerbing 1988) for each type of learning and adaptive selling and learning goal orientation. In all cases, the chi-square difference between the two models for each pair was significant ($\Delta\chi^2 > 3.84$, Δd.f. = 1, $p < .01$), which suggests that the two types of learning are distinct from other similar constructs. We also tested the proposed model by controlling for the effect of adaptive selling on performance. The model with adaptive selling explained an additional 3% of the variance in performance, with no change in the significance of direct and interaction effects.

H_{2b} but not H_{2a}. Capability control is positively related to exploratory learning ($b = .174$, $p < .01$) and negatively related to exploitative learning ($b = –.106$, $p < .05$), in support of both H_{3a} and H_{3b}.

[Insert Table 6 here]

Mediation effects. Our conceptual model hypothesizes the mediating role of salesperson learning. We estimate the indirect effects of control systems on salesperson performance through exploratory and exploitative learning by bootstrapping (1,000 samples) at the 95% confidence level (Zhao, Lynch, and Chen 2010). None of the control systems has a significant direct effect on salesperson performance. However, outcome control has a negative, significant indirect effect on performance through exploratory learning ($b = –.015$, confidence interval [CI] [–.031, –.005], $p < .01$) and a positive, significant indirect effect on performance through exploitative learning ($b = .020$, CI [.006, .043], $p < .05$), in support of H_{4a} and H_{4b}. For activity control, the indirect effect through exploitative learning is positive and significant ($b = .049$, CI [.018, .100], $p < .01$), while the indirect effect through exploratory learning is not ($b = .004$, CI [–.007, .022], n.s.). These findings support H_{5b} but not H_{5a}. Finally, capability control reveals a positive, significant indirect effect on performance through exploratory learning ($b = .037$, CI [.015, .065], $p < .01$) but not through exploitative learning ($b = –.020$, CI [–.056, .001], n.s.), in support of H_{6b} but not H_{6a}.

Interaction effects. In line with H_{7a}, the effect of exploitative learning on performance increases as a salesperson's preference for sales predictability increases ($b = .095$, $p < .01$). Exploitative learning has a stronger positive effect on performance at high levels of preference for predictability ($b = .279$, $p < .01$) than at low levels of preference for predictability ($b = .137$, $p < .05$), in support of H_{7a}. However, the interaction effect of exploratory learning and preference for sales predictability is not significant ($b = .026$, n.s). Thus, the results do not support H_{7b}.

The effect of exploitative learning on salesperson performance increases as customers' purchase-decision-making becomes more complex ($b = .166$, $p < .01$). Exploitative learning is related to performance at low levels of purchase-decision-making complexity ($b = .107$, $p < .05$), but the effect becomes stronger at high levels of purchase-decision-making complexity ($b = .308$, $p < .01$), in support of H_{8a}. The effect of exploratory learning on salesperson performance decreases as purchase-decision-making complexity becomes more complex ($b = –.148$, $p < .05$). Exploratory learning is related significantly to performance at low levels of purchase-decision-making complexity ($b = .263$, $p < .01$) but not at high levels of purchase-decision-making complexity ($b = .083$, n.s.), in support of H_{8b}.

Post-hoc test. We conducted a post-hoc analysis to test the direct, indirect, and total effects on performance and the effect of exploratory and exploitative learning on performance. We detail the test results in Web Appendix D.

Study 2

Purpose and Contribution

Study 1 reinforces the notion that sales control systems are of crucial importance for the effectiveness and efficiency of salespeople and sales organizations. However, Study 1 examines the performance impact of sales control systems by taking a static approach. We still do not know how changes in sales control systems over time influence salesperson performance. Therefore, a dynamic model of sales control systems is needed. As stated earlier, the literature offers mixed results on the performance effect of sales control systems. We speculate that these conflicting findings may partly be due to the static approach taken in studying sales control systems. Examining the sales control systems–performance relationship by taking a dynamic approach might shed light on the contradictory findings in the literature. Thus, the purpose of Study 2 is to examine the relationship between changes in the degree of sales control systems, exploratory/exploitative learning, and performance over time.

Study 2 makes two important contributions. First, we provide empirical evidence as to whether the findings of the conceptual model (Figure 1) tested in Study 1 can be replicated when changes in sales control systems and salesperson performance are taken into consideration. Second, we test whether change in exploratory/exploitative learning is a key mechanism by which change in sales control systems can lead to change in performance.

Sample and Data

For Study 2, we collected new data from a large pharmaceutical firm at two points in time to capture matched salesperson and supervisor responses to the model constructs. We targeted 352 salespeople and 24 supervisors to complete the questionnaire at Time 1. We received 253 and 24 usable responses from salespeople and supervisors, respectively. One year later, we asked all Time 1 respondents to complete the questionnaire again. This yielded usable responses from 214 salespeople and 24 supervisors at Time 2. Salespeople were mostly male (88.8%), with an average age of 34.8 years. A total of 88% held a graduate degree, and they averaged 7 years of territory experience, 6.6 years of firm experience, and 7 years of career experience. Salespeople served an average of 65 customers and received an average of 53.8 hours of training.

Analytical Approach and Results

The analytical approach involved two steps. First, we performed measure validation for the scales based on the salespeople's responses at Time 1 and Time 2. Second, similar to previous studies (e.g., Kumar and Pansari 2016), we tested the proposed links in Figure 1 by considering changes in variables over time by using the growth modeling approach. We provide the details of the analytic approach in Web Appendix E. Next, we present the results.

Main effects. As Table 7 shows, change in outcome control is negatively related to change in exploratory learning ($b = –.162$, $p < .01$) and positively related to change in exploitative learning ($b = .166$, $p < .01$). Change in activity control is not related to change in exploratory learning ($b = .113$, n.s.) but is positively related to change in exploitative learning ($b = .162$, $p < .01$). Change in capability control is positively related to change in exploratory learning ($b = .187$, $p < .01$) but is not related to change in exploitative learning ($b = .053$, n.s.). Changes in exploratory learning ($b = .252$, $p < .01$) and exploitative learning ($b = .478$, $p < .01$) are both positively associated with change in performance.

[Insert Table 7 here]

Mediation effects. Change in outcome control directly affects change in performance ($b = .236$, $p < .01$). While outcome control's indirect effect through change in exploitative learning is positive ($b = .039$, $p < .05$), this effect is negative through change in exploratory learning ($b = –.032$, $p < .05$), suggesting partial mediation through an increased change in exploitative learning and a decreased change in exploratory learning. Change in activity control has no direct effect on change in performance ($b = .163$, n.s.); however, the indirect effect through change in exploitative learning is significant ($b = .038$, $p < .05$), while the same effect through change in exploratory learning is not ($b = .022$, n.s.), suggesting full mediation only through change in exploitative learning. Finally, the direct effect of change in capability control on change in performance is significant ($b = .215$, $p < .01$), as is the indirect effect through change in exploratory learning ($b = .038$, $p < .05$), but not through change in exploitative learning ($b = .013$, n.s.), in support of partial mediation only through change in exploratory learning.

Interaction effects. Change in preference for sales predictability positively moderates change in the exploitative learning–performance link ($b = .469$, $p < .01$) but negatively moderates change in the exploratory learning–performance link ($b = –.315$, $p < .05$). Change in customers' purchase-decision-making complexity positively moderates change in the exploitative learning–performance relationship ($b = .452$, $p < .01$) and negatively moderates the exploratory learning–performance link ($b = –.204$, $p < .05$).

Discussion

Using RFT and regulatory fit as the overarching theoretical framework, this study integrates how different research streams, such as sales control systems and salesperson learning, which have evolved independently despite room for cross-fertilization, can come together to explain the influence of sales control on performance. First, our research introduces two novel constructs to the sales literature: salesperson exploratory and exploitative learning. We demonstrate that exploitative learning and exploratory learning can be encouraged or discouraged, depending on the type of sales control used. Second, we find that each type of control has a dual indirect effect on performance through either exploratory or exploitative learning, with the dual mediation pathways revealing opposite effects (one positive and the other negative). Third, we employ moderators that tap into salesperson and customer characteristics to delineate boundary conditions that shape the salesperson learning–performance linkage.

Theoretical Implications and Extensions

Integrating the literature on sales control and salesperson learning. The sales control and learning literature streams have advanced in parallel without much integration. We attempt to reverse this trend by theorizing and empirically showing that there is an intricate link between the two. Results suggest that (1) when outcome control is used, more exploitative and less exploratory learning occurs; (2) when activity control is used, more exploitative learning occurs; and (3) when capability control is used, more exploratory and less exploitative learning occurs.

If the objective is to have salespeople engage in experimental, creative, risk-taking, and bold endeavors to address customers' needs in different and novel ways, capability control is optimal. On the contrary, if the goal is to encourage salespeople to use safe and proven methods with little ambiguity and risk, outcome or activity control would be more effective. These results extend the regulatory fit literature to the sales context by showing that there is greater alignment between sales control and salesperson learning if a salesperson adopts a more promotion-focused (prevention-focused) learning approach when management is more (less) tolerant of mistakes, uncertainty, and risks and takes a longer-term (shorter-term) perspective. Our research shows that salespeople engage in both types of learning but gravitate toward one more than the other in response to the type of sales control adopted (Jaworski 1988).

Contribution to the link between sales control and salesperson performance. Our study articulates a clear but complicated mediation process between sales control and performance through salesperson learning. The results reveal that outcome and activity controls have negative (positive) indirect effects on performance when mediated by exploratory (exploitative) learning, while capability control has a positive (negative) indirect effect on performance when mediated by exploratory (exploitative) learning. These results show how the dual mediation paths can lead in opposite directions and often result in equivocal and conflicting results depending on the type of learning. Because each control system can have two pathways to performance, either through exploratory or exploitative learning, where one is positive and the other is negative, the two paths may cancel each other out and, in turn, nullify the direct impact of control on performance. Given this new insight, our findings can partially explain the mixed results in the literature pertaining to control systems and performance.

Contribution to the contingency effect of salesperson learning. Performance effects related to the two types of learning we examine depend on salesperson and customer characteristics. Although research has shown that learning efforts lead to greater self-efficacy, the literature is silent on when salesperson learning, let alone different types of learning, results in different levels of performance (Wang and Netemeyer 2002). Building on the reasoning of regulatory fit and in line with the results from Studies 1 and 2, we find that at high (low) levels of preference for predictability, the effect of exploitative learning on performance increases (decreases), while the effect of exploratory learning on performance decreases (increases). At high (low) levels of purchase-decision-making complexity, the effect of exploitative learning on performance also increases (decreases), while the effect of exploratory learning on performance decreases (increased). Collectively, these interaction effects support our theorizing that performance benefits (suffers) from salesperson learning when there is regulatory fit (misfit) between learning and salesperson and customer characteristics.

Contribution to salesperson learning. The marketing literature has emphasized learning at the firm level (e.g., Hurley and Hult 1998). This focus might be responsible for the limited theoretical and practical advancement pertaining to learning at the individual level, despite repeated calls for such research (Tuncdogan, Van Den Bosch, and Volberda 2015). This study is one of the few to examine exploratory and exploitative learning at the salesperson level. Given that individual exploratory and exploitative learning are the micro-foundations for organizational and team-level learning, our study enhances the understanding of the role that a salesperson’s learning plays in higher-level learning within firms. As Argyris and Schon (1978, p. 20) note, “there is no organizational learning without individual learning.”

Managerial Implications

In the pharmaceutical industry, salespeople are getting less face time with physicians. Instead, they are finding themselves in a position of having to convince hospital administrators, who are increasingly acting as gatekeepers of purchase approvals (Rockoff 2014). This paradigm shift is rewriting the rulebooks for salespeople, who must adapt to the turbulent health care environment.

When to use salesperson exploratory or exploitative learning. When a salesperson can sell to a doctor (i.e., a single decision-making unit) rather than to a group of hospital administrators (i.e., a group decision-making unit) or if the salesperson has a high tolerance for generating sales, using exploratory learning is more likely to pay off. However, in complex buying situations, such as new purchases involving multiple people with different roles (e.g., purchaser, influencer), or when the salesperson has a low tolerance for closing sales transactions, exploitative learning will be the preferable mode of learning to enhance salesperson performance.

Understand salesperson and customer characteristics to determine which control system should be used to maximize impact on performance. Given the dual mediating route from sales control to performance, it is important to identify the combination of salesperson and customer characteristics that will produce the greatest impact from each type of sales control on performance and what the dominant salesperson learning is that accounts for how this occurs (see Web Appendix D). For example, we find that outcome and activity controls maximize performance when both preference for sales predictability and purchase-decision-making complexity are high, while capability control benefits performance the most when both preference for sales predictability and purchase-decision-making complexity are low. Furthermore, it is critical to understand that exploitative learning, rather than exploratory learning, is the dominant path through which the impact of outcome and activity control on performance is maximized when both moderators are high. Conversely, exploratory learning is the dominant route through which capability control's effect on salesperson performance is maximized when both moderators are low. Managers need to be cognizant of these difference effects and ensure that the appropriate learning style is aligned with the given type of sales control that is being employed.

Limitations and Future Research Directions

The empirical assessment of our model should be interpreted in light of certain limitations, due in part to trade-off decisions in our research design. We tested our model in the pharmaceutical industry in South Korea, but it will be important to conduct studies beyond this context to assess the generalizability of our findings. We test the proposed model with data collected at the salesperson level. Thus, our findings reflect the variation in the level of exploratory and exploitative learning across salespeople. Yet salespeople perform a variety of tasks. Accordingly, the extent to which salespeople emphasize exploratory and exploitative learning may well depend on the nature (or type) of the task they perform. In this case, the appropriate unit of analysis would be at the task level rather than at the salesperson level, and data collected at the task level may capture variation in the level of exploratory and exploitative learning across tasks more appropriately. Moreover, although not examined in this research, a change in learning over time may be needed, such as from exploitative to exploratory, or vice versa, even for the same doctor.

In addition, we have suggested that because prior studies that have used cognition or attitude as mediators between sales control and salesperson performance have provided limited and inconclusive results, behaviors such as salesperson learning, which is more proximal to salesperson performance, may be the more appropriate mediator. However, our model does not include cognition- or attitude-related mediators, and therefore a more robust and rigorous test would be to include cognition-, attitude-, and behavior-related mediators all in one model.

Furthermore, although it is likely that firms deploy combinations of sales controls (Jaworski, Stathakopoulos, and Krishnan 1993), this study does not focus on interactions between control systems (Miao and Evans 2013) and their impact on salesperson learning. Moreover, our research focuses on formal, as opposed to informal (i.e., self, social, and cultural), controls (Jaworski 1988). It would be enlightening to examine the effects of informal sales controls, as well as combinations of control systems, on salesperson learning.

Finally, because we were not able to obtain objective performance measures, we use a single, subjective generic scale (Behrman and Perreault 1982) to measure salesperson performance. This scale has been used extensively in previous research (e.g., Cravens et al. 1993; Evans et al. 2007; Sujan, Weitz, and Kumar 1994) and is one of the most reliable measures of salesperson (outcome) performance. That said, an objective performance measure (e.g., quota) and/or a measure that is more related to learning would have been ideal.

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TABLE 1
Empirical Research on Salesforce Control Systems and Salesperson Performance

				Type of Control and Its Link to Performance Outcome(s)		
Study/Unit of Analysis	**Sample**	**Performance Outcome(s)**	**Mediating Variables Employed**	**Outcome Control**	**Activity Control**	**Capability Control**
Cravens et al. (1993) • Sales units	144 field sales managers from diverse U.S. sales organizations	Field sales managers' ratings of performance • Selling behavioral performance (technical knowledge, sales presentations) • Nonselling behavioral performance (providing information, controlling expenses) • Outcome performance (achieving sales objectives)	Salesforce characteristics • Professional competence • Team orientation • Risk taking • Intrinsic motivation • Recognition motivation • Planning orientation • Sales support orientation • Customer orientation	• Technical knowledge (0) • Making sales presentations (0) • Providing information (+) • Controlling expenses (0) • Achieving sales objectives (+)	• Technical knowledge (0) • Making sales presentations (+) • Providing information (0) • Controlling expenses (0) • Achieving sales objectives (0)	
Oliver and Anderson (1994) • Sales units	347 salespeople of independently owned/operated sales agencies in the electronics industry	Self-report performance (i.e., sales goals, overall performance, annual sales)			• Relative performance (–) • Sales expense control (+) • Sales presentation/planning (+)	
Babakus et al. (1996) • Sales units	58 chief sales executives and 146 sales managers from 58 companies	• Behavioral performance (i.e., technical knowledge, adaptive selling, teamwork, sales presentation, sales planning, and sales support) • Outcome performance (i.e., achieving sales objectives)	• Territory design		Chief executives' sample • Behavioral performance (+) • Outcome performance (+) Sales managers' sample • Behavioral performance (0) • Outcome performance (0)	
Challagalla and Shervani (1996) • Salesperson	270 salespeople from five industrial product divisions of two Fortune 500 companies	Self-reported performance (achieving sales targets)	• Supervisor role ambiguity • Customer role ambiguity	• Information/punishment (0) • Rewards (–)	• Performance (0)	• Information/rewards (–) • Punishment (0)
Ramaswami, Srinivasan, and Gorton (1997) • Salesperson	165 salespeople of a Fortune 100 organization in the agriculture industry	Supervisor ratings (i.e., performance, business growth, professional growth, overall evaluation)	• Information asymmetry • Dysfunctional behavior	• Performance (0)	• Performance (0)	
Atuahene-Gima, and Li (2002) • Salesperson	Chinese sample: 215 salespeople in high-tech firms U.S. sample: 190 salespeople in	Self-reported performance (i.e., contributing to market share, generating a high level of sales, quickly generating sales from the new product)	• Supervisee trust	Chinese sample • Performance (0) U.S. sample • Performance (+)	Chinese sample • Performance (0) U.S. sample • Performance (+)	

	nonmanufacturing firms					
Menguc and Barker (2003) • Sales Units	102 field sales managers from 47 Canadian organizations	Sales unit performance (i.e., sales volume, profitability, customer satisfaction)		• Sales volume (0) • Profitability (0) • Customer satisfaction (+)	• Sales volume (0) • Profitability (0) • Customer satisfaction (–)	
Fang, Evans, and Landry (2005) • Salesperson	Chinese sample: 308 salespeople from 30 companies U.S. sample: 247 salespeople from 152 sales units	Performance expectations	• Attributional ascriptions (i.e., effort, strategy, ability) • Attributional dimensions (i.e., stable, internal)	Chinese sample • Performance (–) U.S. sample • Performance (0)	Chinese sample • Performance (–) U.S. sample • Performance (0)	Chinese sample • Performance (–) U.S. sample • Performance (0)
Piercy et al. (2006) • Salesperson	214 salespeople in a large, commercial directory publisher	Self-reported performance • Outcome • Behavioral	• Organizational support • Organizational citizenship behaviors		• Outcome performance (0) • Behavior performance (+)	
Evans et al. (2007) • Salesperson	310 salespeople from 82 manufacturing, wholesaling, and services firms	Self-rated outcome performance	• Customer orientation • Sales supportiveness • Sales innovativeness	• Performance (+)	• Performance (0)	• Performance (0)
Ahearne et al. (2010) • Salesperson	226 sales representatives of a pharmaceutical firm	Objective performance (i.e., new product sales)			• Performance (0)	
Schepers et al. (2012) • Service employees	262 customer contact employees of a medical equipment manufacturer's European customer contact center	Supervisor ratings of salesperson in-role performance		• Performance (+)	• Performance (+)	
Miao and Evans (2013) • Salesperson	223 salespeople from manufacturing firms	Self-rated performance (i.e., contributions to market share and dollar sales)	• Job engagement • Job stress	• Performance (0)	• Performance (0)	• Performance (0)

Notes: Studies on the control–performance relationship from the same data set are reported once. (+) denotes a positive relationship, (0) denote a nonsignificant relationship, and (–) denotes a negative relationship.

TABLE 2
Select Studies on Exploratory and Exploitative Learning in Marketing

Study	Sample	Unit of Analysis	Research Context	Position of Exploratory/Exploitative Learning in Conceptual Model	Major Findings
Kyriakopoulos and Moorman (2004)	96 Dutch firms in the food industry	Firm	New product development and marketing strategy	Independent variable moderated by market orientation	• The interaction between exploration and exploitation marketing strategies has a positive (negative) effect on new product financial performance only when market orientation is high (low).
Auh and Menguc (2005)	260 Australian manufacturing firms	Firm	Marketing strategy	Independent variable as antecedents to effective and efficient firm performance	• For both prospectors and defenders, exploration is more positively related to effective firm performance than exploitation. • Exploration (exploitation) has a greater effect than exploitation (exploration) on firm performance for prospectors (defenders). • For defenders (prospectors) at high competitive intensity, exploitation is negatively (positively) related to firm efficiency.
Atuahene-Gima (2005)	227 Chinese electronics firms	Firm	New product innovation (Radical and Incremental)	Mediator between customer and competitor orientations and radical and incremental product innovations	• Competence exploration has a positive (negative) effect on radical (incremental) product innovation. • Competence exploitation has a positive (negative) effect on incremental (radical) product innovation. • Exploration and exploitation mediate the relationships of customer and competitor orientations with radical innovation.
Atuahene-Gima and Murray (2007)	179 Chinese technology new ventures	Firm	New product development	Mediator between structural, relational, and cognitive dimensions of social capital and new product performance	• Intra-industry managerial ties positively affect exploratory and exploitative learning. • Extra-industry managerial ties positively affect exploratory and negatively affect exploitative learning. • Exploratory (exploitative) learning positively (negatively) affects new product performance. • The interaction between exploratory and exploitation learning negatively affects new product performance.
Li, Chu, and Lin (2010)	253 Taiwanese firms mostly in the electronic information industry	Firm	New product development	Independent variable moderated by several moderators (e.g., reward systems, encouragement to take risks, project development formalization)	• Exploratory learning has a positive effect on new product performance when the process reward system is high (vs. low). • Exploitative learning has a positive effect on new product performance when the output reward system is high (vs. low). • Exploratory learning has a positive effect on new product performance when encouragement to take risks is high (vs. low). • Exploitative learning has a positive effect on new product performance when project formalization is high (vs. low).
Vorhies, Orr, and Bush (2011)	169 U.S. firms in the goods and services industry	Firm	Marketing strategy	Mediator between market knowledge development and customer-focused marketing capabilities	• Market knowledge development positively affects marketing exploration and exploitation capabilities. • The interaction between marketing exploration and exploitation capabilities negatively affects customer-focused marketing capabilities.
Yannopoulos, Auh, and Menguc (2012)	216 Canadian high-tech firms	Firm	New product performance	Independent variable moderated by proactive and responsive market orientation	• New product performance suffers when exploratory (exploitative) learning is complemented by responsive (proactive) market orientation. • New product performance improves when exploratory learning is complemented by proactive market orientation.
Mu (2015)	U.S. sample: 324 firms Chinese sample: 569 high-tech firms	Firm	New product development	Mediator between marketing capability and new product development performance	• Exploration and exploitation mediate the relationship between marketing capability and new product development performance (United States and China).

TABLE 3
Definition, Operationalization, and Reference of Key Constructs

Construct	Definition	Operationalization	Source (Reference)
Exploratory learning	A salesperson's self-regulated promotion-focused behavior that searches for, experiments with, and discovers new and innovative selling techniques and skill sets.	A five-item scale (1 = "never," 5 = "always")	New scale
Exploitative learning	A salesperson's self-regulated prevention-focused behavior that adheres to proven and well-established selling techniques and skill sets that leverage known knowledge and capabilities.	A five-item scale (1 = "never," 5 = "always")	New scale
Outcome control	A laissez faire control method in which the salesperson is given the freedom to use whichever method he or she prefers as long as certain outcomes (e.g., sales volume, quota) are achieved.	Salesperson's incentive rate as the ratio of total variable compensation (i.e., total compensation minus base salary) to sales revenue in the last financial year	Lo, Ghosh, and LaFontaine's (2011)
Activity control	A more involved control method from management in which a salesperson is not responsible for outcomes as long as certain procedures and routines (number of sales calls made, number of samples distributed) are followed.	A five-item Likert scale (1 = "strongly disagree," 5 = "strongly agree")	Kohli, Shervani, and Challagalla (1998)
Capability control	A developmental and nurturing control method in which management provides training and guidance to develop and improve a salesperson's skill sets and abilities (presentation skills, client interaction and negotiation skills, relationship management skills).	A five-item Likert scale (1 = "strongly disagree," 5 = "strongly agree")	Kohli, Shervani, and Challagalla (1998)
Preference for sales predictability	A salesperson's trait-like disposition that favors prompt, transparent, expected, and results over opaque, surprise, and delayed outcomes.	A four-item scale (1 = " never," 5 = "always") using one of the dimensions of Webster and Kruglanski's (1994) need-for-closure scale	Choi et al. (2008); Houghton and Grewal (2000)
Customers' purchase-decision-making complexity	The extent to which customers' purchase decision making involves time, information, multiple parties, and new processes.	A five-item scale Likert scale (1 = "strongly disagree," 5 = "strongly agree")	John and Weitz (1989)
Salesperson performance	The degree to which salespeople meet sales objectives.	A seven-item formative scale (1 = "needs improvement," 5 = "outstanding")	Behrman and Perreault (1982)

TABLE 4
Scales and Confirmatory Factor Analyses Results (Study 1)

	Loadings
Salesperson Responses	
(χ^2 = 944.97, d.f. = 499; GFI = .838; TLI = .916; CFI = .925; RMSEA = .049)	
Activity Control	
My immediate manager…	
…informs me about the sales activities I am expected to perform.	.630
…informs me on whether I meet his/her expectations on sales activities.	.690
…evaluates my sales activities.	.792
…monitors my sales activities.	.758
If my immediate manager feels I need to adjust my sales activities, s/he tells me about it.	Deleted
Capability Control	
My immediate manager…	
…evaluates how I make sales presentations and communicate with customers.	.743
…provides guidance on ways to improve selling skills and abilities.	.848
…assists by suggesting why using a particular sales approach may be useful.	.774
…periodically evaluates the selling skills I use to accomplish a task.	.701
My immediate manager has standards by which my selling skills are evaluated.	Deleted
Sales Volatility	
The amount I sell is largely beyond my control.	.782
I have a difficult time in predicting my sales from year to year.	.879
I do not really know how much more I could sell if I worked harder.	.841
Learning Goal Orientation	
An important part of being a good salesperson is continually improving my skills.	.702
It is important for me to learn from each selling experience I have.	.705
There really are not a lot of new things to learn about selling. (R)	Deleted
It is worth spending a great deal of time learning new approaches for dealing with my customers.	.769
Learning how to be a better salesperson is of fundamental importance to me.	.697
I put in a great deal of effort in order to learn something new about serving my customers.	.765
Exploratory Learning	
I search for novel information and ideas that enable me to learn new sales techniques.	.708
I discover new selling techniques that take me beyond my current knowledge, skills, and abilities in improving my performance.	.735
I engage in learning new selling skills and knowledge that help me look at existing customers' problems in a different light.	.706
I explore novel and useful approaches that I can use to respond to customers' needs and wants in the future.	.772
I focus on learning new knowledge of selling techniques that involve experimentation and the potential risk of failure.	.689
Exploitative Learning	
I adhere to sales techniques that I can implement well to ensure productivity rather than those that could lead me to implementation mistakes.	.577
I implement my proven approaches to leverage my existing knowledge and experience in selling to customers.	.755
I adopt sales techniques that suit well to my current knowledge and experience.	.739
I execute those sales techniques that are aligned well with my selling routines.	.802
I prefer undertaking sales tasks with little variation in my performance compared to sales tasks with handsome rewards but with risks involved.	.677
Preference for Sales Predictability	
I feel uncomfortable going into sales situations without knowing what might happen.	.713
I dislike unpredictable sales situations.	.706
I don't like to do business with customers who are capable of unexpected actions.	.766
I don't like to go into sales situations without knowing what I can expect from it.	.724
Customers' Purchase-Decision-Making Complexity	
My customers usually make their purchase decision quickly. (R)	.694
Several people are usually involved in the purchase decision.	.611
My customers usually need a lot of information before purchasing.	.770
My customers usually consider the purchase decision to be routine. (R)	.737
My customers' purchase decision usually evolves over a long period of time,	Deleted
Sales Manager Responses	
Salesperson Performance (Formative Scale)	
This salesperson…	
…produces a high market share for the company in his/her territory.	
…produce sales or blanket contracts with long-term profitability.	
…makes sales of those products with the highest profit margin.	
…generates a high level of dollar sales.	
…quickly generates sales of new company products.	
…identifies and sells to major accounts in his/her territory.	
…exceeds all sales targets and objectives for his/her territory during the year.	

Notes: (R) = reverse scored item, GFI = goodness-of-fit index, TLI = Tucker–Lewis index, CFI = comparative fit index, and RMSEA = root mean square error of approximation.

TABLE 5
Descriptive Statistics, Intercorrelations, and Reliabilities (Study 1)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Company[a]																
2. Sales experience (ln)	–.017															
3. Training (ln hours)	–.574**	.050														
4. Number of customers (ln)	–.322**	.132**	.183**													
5. Sales effort (ln)	–.136**	–.102*	.191**	.159**												
6. Past performance	.075	.163**	–.065	.142**	.068											
7. Learning orientation	–.068	.044	.081	–.035	.127*	.040										
8. Sales volatility	.175**	–.230**	–.227**	.014	–.009	–.129*	–.166**									
9. Preference for predictability	–.046	–.147**	–.117*	.058	.065	–.109*	.121*	.477**								
10. Customers' PDMC	–.040	–.001	–.040	.058	.010	–.150**	.118*	.347**	.302**							
11. Activity control	–.020	–.090	–.090	.090	.013	–.091	.016	.500**	.544**	.342**						
12. Capability control	–.087	–.011	.084	–.144**	.032	.084	.495**	–.050	.171**	.231**	.329*					
13. Outcome control	–.079	–.193**	.074	.015	.004	–.030	–.076	.176**	.125*	.111*	.135**	.038				
14. Exploratory learning	–.051	.062	.102*	–.057	.088	.037	.569**	–.075	.187**	.147**	.053	.448**	–.167**			
15. Exploitative learning	.117*	–.118*	–.070	–.019	.018	–.072	.004	.538**	.310**	.315**	.457**	–.006	.233**	–.023		
16. Salesperson performance	–.246**	.235**	.128*	.198**	.145**	.128*	.405**	.032	.095	.399**	.158**	.323**	.149**	.382**	.168**	
M	—	2.82	3.11	3.87	2.84	3.78	4.05	2.73	3.26	3.28	3.05	3.80	2.84	4.08	3.09	3.53
SD	—	.28	1.18	.71	1.40	1.04	.56	.95	.75	.61	.85	.68	.94	.53	.84	.63
Cronbach's α	—	—	—	—	—	—	.83	.87	.83	.79	.84	.85	—	.83	.83	—
Composite reliability	—	—	—	—	—	—	.85	.87	.82	.80	.81	.85	—	.84	.84	—
Average variance extracted	—	—	—	—	—	—	.53	.70	.53	.50	.52	.59	—	.52	.51	—

*p < .05 (two-tailed test).
**p < .01 (two-tailed test).
[a]Dummy variable (Company A = 1; Company B = 2).
Notes: PDMC = purchase-decision-making complexity. Outcome control (i.e., incentive rate) is natural log-transformed.

TABLE 6
Results (Study 1)

	Main-Effects Model						Full Model					
	Exploratory Learning ($R^2 = .372$)		Exploitative Learning ($R^2 = .368$)		Salesperson Performance ($R^2 = .468$)		Exploratory Learning ($R^2 = .388$)		Exploitative Learning ($R^2 = .377$)		Salesperson Performance ($R^2 = .520$)	
	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE
Paths												
Direct Effects												
Outcome control	–.072**	.020	.107**	.031			–.072**	.020	.107**	.031		
Activity control	.020	.030	.257**	.048			.020	.030	.257**	.048		
Capability control	.174**	.038	–.106*	.070			.174**	.038	–.106*	.070		
Exploitative learning					.224**	.062					.208**	.061
Exploratory learning					.236**	.056					.173**	.055
Moderating Variables												
Preference for predictability					–.094**	.039					–.089*	.038
Customers' PDMC					.351**	.045					.350**	.044
Interaction Effects												
Exploitative learning × Preference for predictability											.095**	.039
Exploratory learning × Preference for predictability											.026	.064
Exploitative learning × Customers' PDMC											.166**	.047
Exploratory learning × Customers' PDMC											–.148*	.075
Controls												
Company (Company A = 1; Company B = 2)	.008	.021	.066*	.033	–.108**	.024	.008	.021	.066*	.033	–.122**	.023
Sales experience	.057	.083	.073	.131	.413**	.092	.057	.083	.073	.131	.366**	.088
Training (ln hours)	.038	.023	.072*	.037	–.023	.026	.038	.023	.072*	.037	–.035	.025
Number of customers (ln)	–.021	.034	–.059	.054	.065	.038	–.021	.034	–.059	.054	.077*	.036
Sales effort (ln)	.007	.016	.006	.026	.035*	.018	.007	.016	.006	.026	.032	.017
Past performance	.003	.022	.011	.035	.077**	.024	.003	.022	.011	.035	.081**	.023
Learning goal orientation	.426**	.046	.175*	.073	.270**	.054	.426**	.046	.175*	.073	.228**	.053
Sales volatility	.025	.028	.362**	.045	.034	.035	.025	.028	.362**	.045	–.025	.036
Endogeneity Correction												
Exploratory learning$_{residual}$					–.087	.062					–.079	.065
Exploitative learning$_{residual}$					-.087*	.037					–.090*	.037

Fit Statistics
The main effects model: (χ^2 = 3.304, d.f. = 3; GFI = .999; TLI = .993; CFI = 1.0; RMSEA = .016)
The interaction model: (χ^2 = 4.110, d.f. = 3; GFI = .999; TLI = .969; CFI = 1.0; RMSEA = .031)

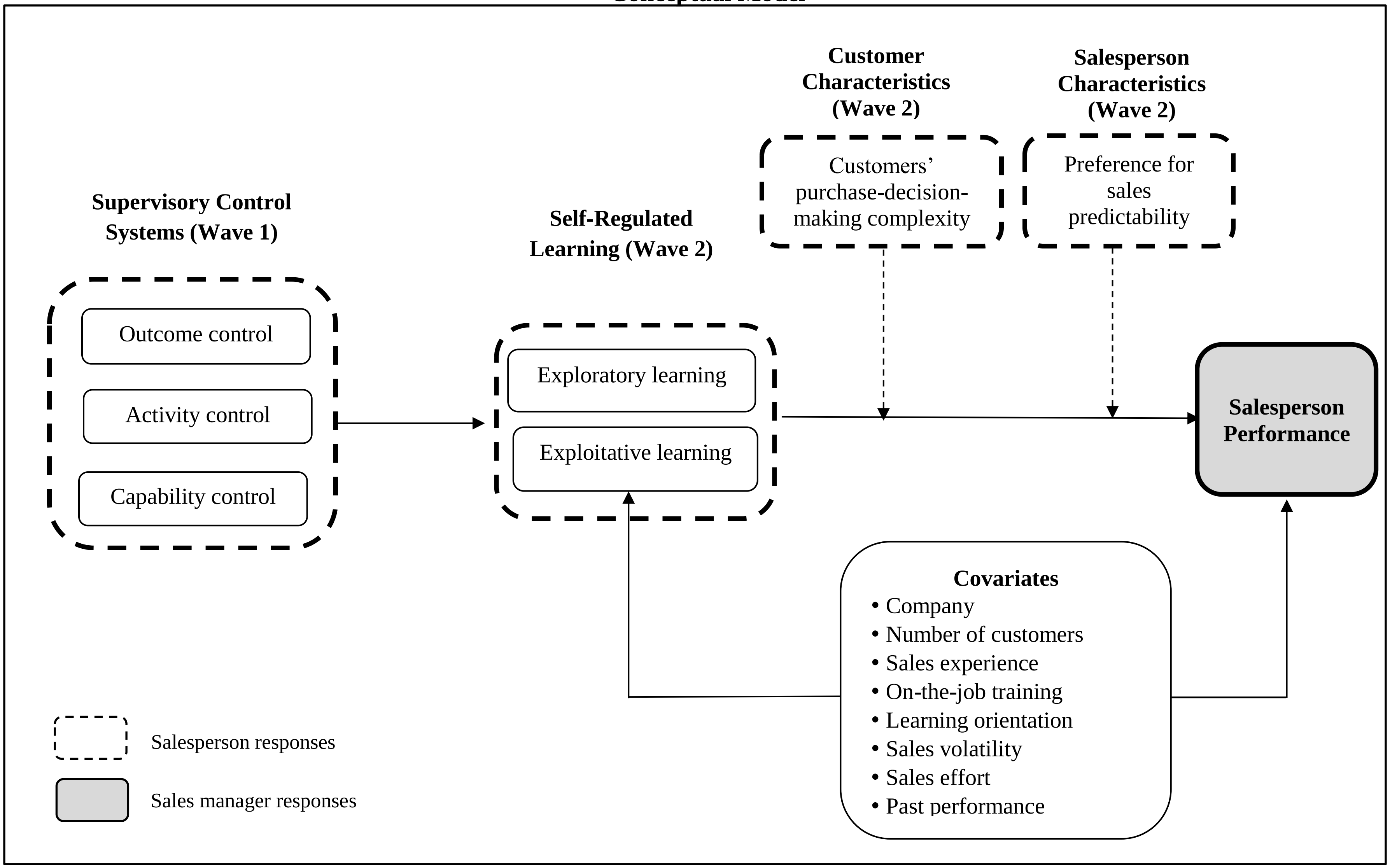
*p < .05 (one-tailed test for hypothesized, directional relationships; two-tailed test for control variables).
**p < .01 (one-tailed test for hypothesized, directional relationships; two-tailed test for control variables).
Notes: Unstandardized coefficients and standard errors with Monte Carlo integration (1,000 bootstraps) are reported. PDMC = purchase-decision-making complexity. GFI = goodness-of-fit index, TLI = Tucker–Lewis index, CFI = comparative fit index, and RMSEA = root mean square error of approximation.

TABLE 7
Results (Study 2)

	Main-Effects Model						**Full Model**					
	ΔExploratory learning		**ΔExploitative learning**		**ΔSales Performance**		**ΔExploratory learning**		**ΔExploitative learning**		**ΔSales Performance**	
	b	**SE**	**b**	**SE**	**b**	**SE**	**b**	**SE**	**b**	**SE**	**b**	**SE**
Direct Effects												
ΔOutcome control	–.162**	.058	.166**	.052			–.162**	.058	.166**	.052		
ΔActivity control	.113	.074	.162**	.066			.113	.074	.162**	.066		
ΔCapability control	.187**	.053	.053	.047			.187**	.053	.053	.047		
ΔExploitative learning					.252**	.107					.478**	.111
ΔExploratory learning					.195*	.094					.252**	.090
Additional Paths												
ΔOutcome control					.274**	.076					.239**	.072
ΔCapability control					.190**	.070					.167**	.067
Moderating Variables												
Preference for predictability					.069	.072					.151*	.072
ΔCustomers' PDMC					–.105	.089					.051	.089
Interaction Effects												
ΔExploitative learning × Preference for predictability											.469**	.107
ΔExploratory learning × Preference for predictability											–.315*	.142
ΔExploitative learning × ΔCustomers' PDMC											.452**	.160
ΔExploratory learning × ΔCustomers' PDMC											–.204*	.123
Controls												
ΔSales volatility	.075*	.038	–.014	.033	.043	.089	.075*	.038	–.014	.033	.059	.050
Learning goal orientation	.006	.060	–.144**	.053	.095	.052	.006	.060	–.144**	.053	.075	.086
Adjusted R^2	.234		.253		.159		.234		.253		.248	

*p < .05 (one-tailed test for directional relationships, two-tailed test for control variables).
**p < .01 (one-tailed test for directional relationships, two-tailed test for control variables).
Notes: Model Fit (Main Effects Model: χ^2 = 2.292, d.f. = 1; GFI = .998; TLI = .938; CFI = .996; RMSEA = .068; Full Model: χ^2 = 1.792, d.f. = 1; GFI = .999; TLI = .934; CFI = .999; RMSEA = .052). Unstandardized coefficients and standard errors with Monte Carlo integration (1,000 bootstraps) are reported. PDMC = purchase-decision-making complexity.

FIGURE 1
Conceptual Model



Notes: Sales managers' evaluations of salesperson performance were gathered three weeks after Wave 2 was completed.

WEB APPENDIX A
Interview Results

The following interview excerpt provides an example of exploratory learning:

> "Doctors sometimes see ten or more sales reps in a given day and we only have 5-10 minutes to get their attention. Therefore, we have to stand out to have any chance. Although risky because I am pushed to go beyond my comfort zone, I try to remove my salesperson hat and put on a scientist hat. This approach allows me to interact and show doctors that I am not simply a salesperson but someone that is versed in medical research and has deep knowledge in drugs and science. I actually have to invest in extra research to engage in an intellectual conversation with doctors that go beyond mere drug benefits and side effects. My goal is to earn trust and credibility in what I do. However, this entails uncertainty and can backfire because I have to walk a fine line and be cautious not to intrude on the authority of the doctor due to Korea being a high power distance society. Stepping over this line and giving the impression that I know more can have grave consequences."

The following interview excerpt is an example of exploitative learning:

> "When I meet with doctors to sell drugs, I have always focused on the product and only on the product. I stick with delivering information about the drug such as its efficacy and how it is different from the competition. I understand that such a selling approach may not leave a lasting impression on the doctor because it is a common and standard method used by many other salespeople. I realize that it may benefit me if I expand and experiment with new selling techniques but I like to stick to the status quo by using a more scripted approach and avoid making mistakes that can risk my sales performance. I feel comfortable with a product centered selling approach and for the most part it has worked fairly well for me. I do not feel confident trying out other new methods that may hurt my sales or jeopardize my relationship with doctors."

WEB APPENDIX B
Control Variables (Study 1)

We wanted to ensure that our model is stable and that the hypothesized relationships explain additional variance even after controlling for other factors that may provide alternative explanations (Spector and Brannick 2011). Theoretically and methodologically relevant control variables also mitigate self-selection and omitted variables biases.

Salesperson learning might be influenced by a range of factors, such as individual differences (i.e., demographics), motivation (i.e., goal orientations), supervision styles, and work environment (e.g., Cron et al. 2005). We controlled for the effects of sales experience, number of customers served, learning goal orientation, sales volatility, and past performance when we estimated exploratory and exploitative learning and performance. In addition, the variation in learning and performance might also be due to salespeople selling different drugs and product lines to different sets of customers, which may require specific training and more sales effort. We therefore control for on-the-job training and sales effort to capture product line–level variation in the level of learning and performance.

We had salespeople assess on-the-job training (i.e., hours), sales experience (i.e., years in the sales profession), number of customers, and sales effort (i.e., average number of sales calls per week) (Ahearne et al. 2010). We made log transformations to the raw values because they were not normally distributed. We measured sales volatility with a three-item scale adapted from John and Weitz (1989). We captured learning orientation with a six-item scale (Sujan, Weitz, and Kumar 1994). In addition to its predictive value, we use learning orientation as a surrogate for regulatory focus because such an orientation is linked positively to promotion and prevention focus (Wallace, Johnson, and Frazier 2009). Sales managers assessed salespeople's past performance in terms of average sales growth over the past 24 months (1 = sales have declined, 2 = 0%–4% per year, 3 = 5%–9% per year, 4 = 10%–14% per year, 5 = 15% per year or greater).

WEB APPENDIX C
Model Estimation (Study 1)

Measurement Error

We employed path analysis to test our model. The intraclass correlation coefficient, ICC(1), for salesperson performance (.13) was not significant, suggesting independence among multiple salespeople rated by the same sales manager. Thus, nested data analysis was not necessary, and the use of path analysis was appropriate to test our model. Path analysis offers a remedy when the 5:1 ratio of sample size to number of estimated parameters is not met, and it is more effective than ordinary least squares because it accounts for measurement error. We formed a single indicator for each construct by aggregating the scale items (e.g., Brown and Peterson 1994).

We created the interaction terms by mean-centering the respective variables. This procedure facilitates interpretation of the interaction terms along with main effects and minimizes multicollinearity. Multicollinearity was not an issue, because variance inflation factors were below the value of 10 (highest = 2.399). (Aiken and West 1991). We also used Bornstedt and Marwell's (1978) formula of reliability [$r_{xy \cdot xy} = [(r_{xx} \times r_{yy}) + r_{xy}^2]/(1 + r_{xy}^2)$] to compute the reliability score for each interaction term.

We fixed each path from a latent construct to its observed indicator to the value of the square root of the latent construct's reliability (Brown and Peterson 1994). Because interaction effects are not, by their nature, normally distributed, maximum likelihood estimation produces biased estimations. We overcome this limitation by testing the model with Monte Carlo integration (1,000 bootstraps) (Carson 2007).

Alternative Models

We ran two alternative models: the ratio and the nonlinear effects models. First, although common method bias was not a major concern, another way of addressing the inflation of salespeople's responses to exploratory or exploitative learning items is to use a ratio variable (i.e., exploitative/exploratory learning). The ratio variable offers a remedy for self-inflation and accounts for heterogeneity in salespeople's effort. Second, salespeople might not invest their time, effort, and energy fully in exploratory or exploitative learning due to diminishing performance returns, which might require testing the quadratic terms of exploratory and exploitative learning on performance. We find that neither the ratio mediator nor the nonlinear effects were significantly related to performance. A comparison of the Bayesian information criterion (BIC) suggests that the proposed model (BIC = 795.715) has a better fit than the ratio (BIC = 896.570) and the nonlinear effects (BIC = 1,003.244) models.

Endogeneity of Exploratory and Exploitative Learning

Salespeople's decisions to allocate their time, effort, and resources in learning are likely to be driven by their expectations of achieving higher levels of performance. Thus, both exploratory and exploitative learning may be endogenous to other variables that are excluded from the model. As in previous studies (Saboo et al. 2017; Sridhar and Srinivasan 2012), we corrected for endogeneity bias by taking the control function approach (Petrin and Train 2010), an extension of Garen's (1984) procedure. This approach requires an exogenous variable for each learning behavior that meets the requirements of relevance (i.e., correlated with respective type of learning) and exclusion restriction (i.e., uncorrelated with the error term in performance) (Antia, Mani, and Wathne, 2017).

We introduced exploratory and exploitative learning behaviors of coworkers supervised by the same sales manager, a proxy measure of role modeling, as excluded variables for a salesperson's exploratory and exploitative learning. As social learning theory (Bandura 1986) posits, salespeople are likely to observe their coworkers' behaviors, especially when they operate within a work group. In other words, coworkers may serve as role models. In turn, observing coworkers engaging in exploratory and exploitative learning at work may lead a salesperson to adopt certain learning behaviors, a phenomenon known as observational learning. We also expect coworkers' learning behaviors to affect a salesperson's own performance only through a salesperson's own learning behaviors (i.e., not a direct effect).

These variables meet the requirements of relevance (i.e., they are related to a focal salesperson's own learning) and exclusion restriction (i.e., they do not have direct effects on a focal salesperson's performance). The excluded variables are correlated with exploratory learning ($r_{\text{coworkers' exploratory learning}} = .22$) and exploitative learning ($r_{\text{coworkers' exploitative learning}} = .17$) but are not correlated with salesperson performance ($r_{\text{coworkers' exploratory learning}} = .04$, $r_{\text{coworkers' exploitative learning}} = –.02$). In addition, the Sargan test supports the null hypotheses ($\chi^2_{\text{coworkers' exploratory learning}} = 4.29$, $p > .10$; $\chi^2_{\text{coworkers' exploitative learning}} = 3.97$, $p > .10$) such that the two variables were exogenous. Then, we computed the residual for each learning behavior by regressing them against the respective exclusion variable along with two variables in the model: preference for predictability and customer purchase-decision-making complexity. As a result, each learning behavior became uncorrelated with the error term in salesperson performance. The Anderson-Rubin test indicated that the error term was uncorrelated with the excluded variables ($F = 3.61$, $p < .05$). We entered the residual of each learning behavior in the model along with all other variables, through which we controlled for endogeneity bias.

WEB APPENDIX D
Post-Hoc Test

When both moderators are at the mean level, the indirect effects of outcome control on salesperson performance via exploitative learning and exploratory learning are .019 and –.010, respectively, suggesting that both paths play a dominant role. The indirect effects of activity control on salesperson performance via exploitative learning and exploratory learning are .046 and .003, respectively. The dominant indirect path from activity control to performance occurs through exploitative learning rather than through exploratory learning. The indirect effects of capability control on salesperson performance via exploitative learning and exploratory learning are –.010 and .025, respectively, suggesting that both paths play a dominant role.

The performance effect of exploratory learning is highest (lowest) when preference for sales predictability is high (low) and customers' purchase-decision-making complexity is low (high). The direct effect of exploitative learning on performance is highest (lowest) when preference for sales predictability is high (low) and customers' purchase-decision-making complexity is high (low).

When both moderators are high (this is when the combined indirect effects are maximized), the indirect effects of outcome and activity control on salesperson performance via exploitative learning are .038 and .092, respectively, while the indirect effects through exploratory learning are –.001 and .001, respectively. Therefore, the dominant indirect path from outcome and activity control to performance occurs through exploitative learning rather than through exploratory learning. However, we find the opposite for the indirect effect of capability control on performance. When both moderators are low (this is when the combined indirect effects are maximized), the indirect effect through exploitative learning is –.003, while the indirect effect through exploratory learning is .042. Therefore, the dominant indirect path from capability control to salesperson performance occurs through exploratory learning rather than through exploitative learning. Finally, the total effect of outcome and activity control (.058 and .115, respectively) on performance is highest when both preference for sales predictability and purchase-decision-making complexity are high, while capability control (.100) benefits performance the most when both preference for sales predictability and purchase-decision-making complexity are low.

WEB APPENDIX D

TABLE D1
Analysis of Direct, Indirect, and Total Effects

A: Outcome Control (X1 = Outcome Control, M1 = Exploratory Learning, M2 = Exploitative Learning, Y = Salesperson Performance)

Moderating Variables		**Direct Effects**					**Indirect Effects**			**Total Effect**
Preference for Predictability	**PDMC Complexity**	**(X1 → M1)**	**(X1 → M2)**	**(M1 → Y)**	**(M2 → Y)**	**(X1 → Y)**	**Through M1**	**Through M2**	**Through (M1 + M2)**	
Mean	Mean	–.072** [–.106, -.039]	.107** [.058, .164]	.166** [.070, .260]	.198** [.094, .300]	.025 [–.013, .063]	–.010** [–.022, –.003]	.019* [.008, .039]	.009 [–.006, .029]	.034 [–.008, .076]
Low	Low	–.072** [–.106, –.039]	.107** [.058, .164]	.240** [.117, .361]	026 [–.087, .148]	.025 [–.015, .062]	–.017** [–.032, –.007]	.003 [–.010, .019]	–.014 [–.033, .003]	.010 [–.033, .052]
Low	High	–.072** [–.106, –.039]	.107** [.058, .164]	.056 [–.115, .225]	.225** [.089, .369]	.025 [–.015, .062]	–.005 [–.020, .006]	.024** [.010, .050]	.020 [–.001, .046]	.045* [.002, .091]
High	Low	–.072** [–.106, –.039]	.107** [.058, .164]	.276** [.134, .417]	.172** [.042, .301]	.025 [–.015, .062]	–.018** [–.035, –.007]	.015* [.002, .036]	-.001 [–.020, .022]	.023 [–.023, .070]
High	High	–.072** [–.106, –.039]	.107** [.058, .164]	.092 [–.055, .237]	.371** [.260, .482]	.025 [–.015, .062]	–.001 [–.011, .011]	.038** [.021, .066]	.033* [.011, .060]	.058* [.014, .106]

B: Activity Control (X2 = Activity Control, M1 = Exploratory Learning, M2 = Exploitative Learning, Y = Salesperson Performance)

Moderating Variables		**Direct Effects**					**Indirect Effects**			**Total Effect**
Preference for Predictability	**PDMC Complexity**	**(X2 → M1)**	**(X2 → M2)**	**(M1 → Y)**	**(M2 → Y)**	**(X2 → Y)**	**Through M1**	**Through M2**	**Through (M1 + M2)**	
Mean	Mean	.020 [–.026, .070]	.257** [.174, .337]	.166** [.070, .260]	.198** [.094, .300]	.018 [–.042, .076]	.003 [–.003, .015]	.046** [.019, .081]	.054** [.025, .092]	.072* [.007, .136]
Low	Low	.020 [–.026, .070]	.257** [.174, .337]	.240** [.117, .361]	026 [–.087, .148]	.018 [–.042, .076]	.005 [–.006, .021]	.008 [–.022, .040]	.011 [–.018, .045]	.029 [.036, .091]
Low	High	.020 [–.026, .070]	.257** [.174, .337]	.056 [–.115, .225]	.225** [.089, .369]	.018 [–.042, .076]	.001 [–.002, .016]	.059** [.024, .106]	.059** [.024, .107]	.077* [.007, .138]
High	Low	.020 [–.026, .070]	.257** [.174, .337]	.276** [.134, .417]	.172** [.042, .301]	.018 [–.042, .076]	.005 [–.007, .022]	.035* [.001, .073]	.050** [.014, .094]	.068 [–.004, .140]
High	High	.020 [–.026, .070]	.257** [.174, .337]	.092 [–.055, .237]	.371** [.260, .482]	.018 [–.042, .076]	.001 [–.004, .008]	.092** [.055, .136]	.097** [.058, .144]	.115** [.043, .183]

C: Capability Control (X3 = Capability Control, M1 = Exploratory Learning, M2 = Exploitative Learning, Y = Salesperson Performance)

Moderating Variables		Direct Effects					Indirect Effects			Total Effect
Preference for Predictability	PDMC complexity	(X3 → M1)	(X3 → M2)	(M1 → Y)	(M2 → Y)	(X3 → Y)	Through M1	Through M2	Through (M1 + M2)	
Mean	Mean	.174** [.116, .233]	–.106* [–.206,–.002]	.166** [.070, .260]	.198** [.094, .300]	.061 [–.016, .136]	.025** [.009, .047]	–.018* [–.049,–.002]	.008 [–.022, .041]	.069 [–.007, .147]
Low	Low	.174** [.116, .233]	–.106* [–.206,–.002]	.240** [.117, .361]	026 [–.087, .148]	.061 [–.016, .136]	.042** [.020, .072]	–.003 [–.025, .007]	.039** [.012, .076]	.100* [.022, .178]
Low	High	.174** [.116, .233]	–.106* [–.206,–.002]	.056 [–.115, .225]	.225** [.089, .369]	.061 [–.016, .136]	.013 [–.018, .045]	–.024* [–.062,–.002]	–.014 [-.065, .027]	.047 [–.032, .128]
High	Low	.174** [.116, .233]	–.106* [–.206,–.002]	.276** [.134, .417]	.172** [.042, .301]	.061 [–.016, .136]	.044** [.018, .078]	–.015 [–.046, .000]	.030 [–.008, .072]	.091* [.007, .173]
High	High	.174** [.116, .233]	–.106* [–.206,–.002]	.092 [–.055, .237]	.371** [.260, .482]	.061 [–.016, .136]	.016 [–.026, .027]	–.038* [–.079,–.001]	–.023 [–.071, .027]	.038 [–.049, .116]

*p < .05 (one-tailed test).

**p < .01 (one-tailed test).

Notes: Low = 1 standard deviation lower than the mean value of the moderating variable. High = 1 standard deviation higher than the mean value of the moderating variable. Lower and upper limit of confidence intervals are reported in brackets. Bootstrapped (1,000 samples) values are reported. PDMC = customers’ purchase-decision-making complexity.

WEB APPENDIX E
Analytical Approach (Study 2)

Measurement Models and Metric Equivalence

We performed measure validation for the scales based on the salespeople's responses at Time 1 and Time 2. Measurement model for Time 1 included the scales of activity control, capability control, exploratory learning, exploitative learning, preference for predictability, purchase decision-making complexity, sales volatility, and learning goal orientation. Because we define preference for predictability and learning goal orientation as trait-like variables, we consider them time-invariant (i.e., no change over time) and measure them only at Time 1. Therefore, the measurement model for Time 2 included the scales of activity control, capability control, exploratory learning, exploitative learning, purchase-decision-making complexity, and sales volatility.

After we deleted items with low loadings (one item from learning orientation, one from customers' decision-making complexity, and one from preference for sales predictability), the model for Time 1 showed good fit ($\chi^2_{(674)}$ = 1,018.61, goodness-of-fit index [GFI] = .890, Tucker–Lewis index [TLI] = .902, comparative fit index [CFI] = .901, root mean square error of approximation [RMSEA] = .049). Similarly, the model for Time 2 indicated good fit ($\chi^2_{(390)}$ = 619.124, GFI = .838, TLI = .910, CFI = .919, RMSEA = .053). Loadings were significant, reliabilities were above .70, and average variance extracted values were greater than .50 (see Table E1) and above their respective squared correlations, suggesting convergent and discriminant validity (Bagozzi and Yi 1988; Fornell and Larcker 1981). Multigroup confirmatory factor analyses (CFAs) for the scales used in both Time 1 and Time 2 confirmed metric equivalence because the difference between the constrained (i.e., invariant factor structure) and the unconstrained (i.e., variant factor structure) models was not significant ($\Delta\chi^2_{(45)}$ = 51.6, n.s.).

Model Estimation

There are two approaches to calculate temporal change. The first approach is to subtract the Time 1 score from the Time 2 score to obtain a simple change score. The second approach is to calculate change as a slope by using the Bayes estimates in mixed-effects growth models (e.g., Chen et al. 2011). We employ the growth modeling approach because the nested, time-varying nature of the variables (i.e., correlated residuals) violates the independence assumption of ordinary least squares. As Chen et al. (2011) suggest, the growth modeling approach generates accurate scores for each salesperson that are weighted by overall sample information and the salesperson's own information. After change scores are computed, an ordinary least squares–like technique can be used to test the links between the change variables (Chen et al. 2011).

Accordingly, we operationalized change in a given variable as the time-varying slope of that variable (Chen et al. 2011). We estimated the within-person effect of time (Time 1 = 0, Time 2 = 1) on the variables using mixed effect growth modeling (Bliese and Ployhart 2002). For example, the change in exploratory learning was estimated in HLM 7.0 (Raudenbush et al. 2011) as follows:

(E1) Level 1: $EXPLORE_{ij} = \pi_{0j} + \pi_{1j} (TIME) + r_{ij*}$

(E2) Level 2: $\pi_{0j} = \beta_{00} + u_{0j*}$

$\pi_{1j} = \beta_{10} + u_{1j*}$,

where
i = the number of salespeople,
j = time (j = 2),
r_{ij*} = residual (Level 1), and
u_{oj} ,u_{1j} = residuals (Level 2).

Note that the output produced the Bayes estimated slope, which represents change in exploratory learning for each salesperson (Drescher et al. 2014). The more positive (negative) the slope, the greater the increase (decrease) in exploratory learning over time. We repeated the same procedure for all variables in the model except trait-like variables (i.e., learning goal orientation and preference for predictability). As we stated previously, preference for predictability and learning goal orientation are defined as trait-like variables. Therefore, we do not compute their time-varying slope.

We include learning goal orientation (i.e., time-invariant) and change in sales volatility (i.e., time-variant) as covariates due to their theoretical and statistical relationships with changes in learning types and performance. Because demographics are not related to changes in learning types and performance, there is no need to add time-invariant controls in the model estimation. Note that we checked all variables for autocorrelation and heteroskedasticity (Bliese and Ployhart 2002). Autocorrelation was not a concern, but we controlled for heteroskedasticity in estimating the two learning types and performance.

After we saved all the change scores necessary to run the model, we used a path-analytic approach to test direct and interactive links simultaneously. First, we tested the main-effects-only model. Second, we tested mediation effects based on main-effects-only model. Finally, we entered interaction effects into the model to test the full model.

Model Equations (Study 2)

The specific equations used to test the hypotheses in Study 2 are as follows:

$$\Delta EXPLORE_i = b_{10} + b_{11}*\Delta OUTCOME_i + b_{12}*\Delta ACTIVITY_i + b_{13}*\Delta CAPABILITY_i + b_{14}*\Delta VOLATILITY_i + b_{15}*LEARN_i + e_1$$

$$\Delta EXPLOIT_i = b_{20} + b_{12}*\Delta OUTCOME_i + b_{22}*\Delta ACTIVITY_i + b_{23}*\Delta CAPABILITY_i + b_{24}*\Delta VOLATILITY_i + b_{25}*LEARN_i + e_2$$

$$\Delta PERF_i = b_{30} + b_{31}*\Delta EXPLORE_i + b_{32}*\Delta EXPLOIT_i + b_{33}*PREDICT_i + b_{34}*\Delta DECISION_i + b_{35}*\Delta EXPLORE_i*PREDICT_i + b_{36}*\Delta EXPLORE_i*\Delta DECISION_i + b_{37}*\Delta EXPLOIT_i*PREDICT_i + b_{38}*\Delta EXPLOIT_i*\Delta DECISION_i + b_{14}*\Delta VOLATILITY_i + b_{15}*LEARN_i + e_3,$$

where
$\Delta EXPLORE_i$ = change in exploratory learning between time t_1 and time t_2 for salesperson i,
$\Delta EXPLOIT_i$ = change in exploitative learning between time t_1 and time t_2 for salesperson i,
$\Delta OUTCOME_i$ = change in outcome control between time t_1 and time t_2 for salesperson i,
$\Delta ACTIVITY_i$ = change in activity control between time t_1 and time t_2 for salesperson i,
$\Delta CAPABILITY_i$ = change in capability control between time t_1 and time t_2 for salesperson i,
$\Delta PERF_i$ = change in performance between time t_1 and time t_2 for salesperson i,
$\Delta DECISION_i$ = change in purchase decision-making complexity between time t_1 and time t_2 for salesperson i.
$PREDICT_i$ = preference for predictability in time t_1 for salesperson i,
$\Delta VOLATILITY_i$ = change in sales volatility between time t_1 and time t_2 for salesperson i,
$LEARN_i$ = learning orientation in time t_1 for salesperson i,
e_1, e_2, and e_3 = error terms in the respective models, and
i = the number of salespeople.

TABLE E1
Reliabilities and Significance of Time Effect (Study 2)

	Mean Differences			α		CR		AVE				Time Effect		
Variables	**T1**	**T2**	**t-Value**	**T1**	**T2**	**T1**	**T2**	**T1**	**T2**	**ICC_1**	**ICC_2**	**γ**	**SE**	**t-Value**
Outcome control	.28	.30	.83	—	—	—	—	—	—	.38	.82	–.045	.051	.379
Activity control	3.81	3.77	–.91	.82	.88	.84	.88	.52	.59	.48	.87	–.040	.044	–.909
Capability control	3.72	3.69	–.55	.83	.86	.84	.86	.51	.55	.39	.83	–.031	.054	–.574
Exploratory learning	3.71	3.80	2.24*	.88	.88	.88	.88	.51	.52	.54	.90	.099	.040	2.475**
Exploitative learning	3.63	3.71	2.21*	.86	.86	.88	.88	.51	.52	.44	.85	.073	.036	2.028*
Customers' PDMC	3.70	3.60	–2.02*	.76	.78	.76	.79	.52	.56	.28	.74	–.101	.049	–2.061*
Sales volatility	2.76	2.92	2.11*	.88	.87	.88	.88	.71	.79	.48	.87	.129	.064	2.016*
Salesperson performance	3.41	3.51	2.46**	.86	.85	.88	.87	.51	.50	.46	.86	.085	.041	2.073*
Preference for predictability	3.25	—	—	.79	—	.81	—	.52	—	—	—	—	—	—
Learning orientation	3.94	—	—	.86	—	.86	—	.56	—	—	—	—	—	—

*p < .05.
**p < .01.
Notes: T1 = Time 1, T2 = Time 2, α = Cronbach's alpha, CR = composite reliability, AVE = average variance extracted, ICC_1 = interclass correlation (between-person variability), ICC_2 = reliability of person level means, SE = standard error, and PDMC = purchase-decision-making complexity.

WEB APPENDIX F
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