SALES TECHNOLOGY ORIENTATION, INFORMATION EFFECTIVENESS, AND SALES PERFORMANCE

Gary K. Hunter and William D. Perreault Jr.

Sales managers need a practical means for evaluating returns from investments in sales technology implementations (including sales automation and sales-based customer relationship management systems). This research proposes a behavioral process model approach that can be applied to evaluate sales technology implementations. We develop and test the model with data collected from the sales force of a major consumer packaged goods company. The results indicate that a salesperson's technology orientation has a direct impact on internal role performance, and it affects performance with customers through a double-mediated mechanism involving the effective use of information and smart selling behaviors (planning and adaptive selling). Sales managers can influence sales technology orientation by providing better internal technology support, considering technology orientation along with customer's approval of technology in account assignments, and understanding the probability of negative effects through a salesperson's experience. In our sample, salesperson experience correlates with age, suggesting a "generation gap" effect on sales technology orientation.

In the sales and marketing literatures, there has been increasing attention paid to the role of shared information, operational linkages, and cooperation as firms in business markets shift to more closely coupled relationships (cf. Cannon and Perreault 1999). Concurrent with these shifts in the relationships among firms, there has been a reinvention of the traditional sales role. With an increased emphasis on relationship marketing strategies (Anderson 1996), the sales rep has a responsibility to serve as a consultant to the customer and to strengthen the buyer–seller relationship by helping to develop the customer's business and achieve customer satisfaction (Liu and Leach 2001). To enhance sales performance and buyer–seller relationships, firms in a wide variety of industries—ranging from consumer package goods (CPG) and financial services to chemicals and energy—have made substantial investments in information technology (Shoemaker 2001). Unfortunately, these investments continue to be vendor driven, resulting in a high failure rate. The situation is so grim that recent academic research characterizes sales technology implementations as a virtual "minefield" (Speier and Venkatesh 2002). Under such circumstances, it is not surprising that a "day of reckoning" follows such investments in which astute sales managers need to be in a position to justify their investments (Erffmeyer and Johnson 2001).

This paper proposes using a diagnostic approach for composing and testing process models that link desired outcomes with the behavioral tasks that influence them. The approach builds on the long-standing tradition of modeling salesperson behaviors in the sales force and channels literatures (cf. Behrman and Perreault 1984; Brown and Peterson 1993). Specifically, we develop and advance hypotheses about how a salesperson's orientation toward information technology affects two facets of performance—effectiveness in dealing with customers and efficiency in performing internal tasks (such as recommending how company operations can be improved). In this regard, the model posits both indirect and direct positive impacts from a stronger technology orientation by the salesperson.

In this paper, we argue that sales reps with greater technology orientations are better able to leverage information (i.e., make available information more effective), which should, in turn, facilitate sales planning and adaptive behaviors—smart selling behaviors (tasks) that are known to be related to effective selling (cf. Spiro and Weitz 1990). Simply put, we propose a means for assessing "how" sales technology implementations

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affect key aspects of sales performance that are important for sales managers when evaluating salespeople in a modern relational context.

INFORMATION TECHNOLOGY, SALES AUTOMATION, AND SALES–CRM RESEARCH

While there is an extensive and growing literature on information technology, sales automation, and sales-based customer relationship management (CRM), we focus here on research that is most relevant to this study to help frame and position our perspectives. There is a substantial body of excellent research on the impact of information technology on business performance that is relevant to our investigation of the effects of sales technology on sales performance. Several researchers have addressed the relationship between information technology and organizational performance by modeling important organizational inputs such as dollar investments in information technology, and outputs such as financial returns (cf. Bharadwaj, Bharadwaj, and Konsynski 1999). Most of the work that directly models the impact of information technology implicitly treats the organization as a "black box"—so the impact of information technology on individual tasks, specific processes, or intermediate outcomes (such as the quality of services) is not explicitly evaluated.

A second major stream of research on the impact of information technology relies on user evaluations, as opposed to financial returns, to measure the success of information technology. One reason to move to this approach is that a financial investment in a particular technology does not assure that it is used as intended by members of the organization. Thus, there is a long-standing tradition of finding ways through which salespeople can optimize individual sales technology applications. *JPSSM* published an insightful and forward-looking series of papers on applications in personal selling and sales management (for examples, see Collins 1984, 1985, 1989; Comer 1981–82; Swenson and Parrella 1992) and on the role sales managers and salespeople perform in the firm's marketing information systems (Evans and Schlacter 1985; Klompmaker 1980–81). However, renewed interests in sales technology have spawned an emerging literature that focuses on two areas: sales–CRM (Ahearne, Srinivasan, and Weinstein 2004; Pass, Evans, and Schlacter 2004; Plouffe, Williams, and Leigh 2004; Shoemaker 2001; Zablah, Bellenger, and Johnston 2004) and sales automation technologies (Jones, Sundaram, and Chin 2002; Parthasarathy and Sohi 1997; Pullig, Maxham, and Hair 2002; Schillewaert et al. 2005; Speier and Venkatesh 2002).

The burgeoning literature and use of CRM tools has been so pervasive in modern practice that CRM has evolved as both a business philosophy and a technology (Johnston and Marshall 2005, p. 128; see Plouffe, Williams, and Leigh 2004 for varying definitions of CRM across stakeholders). CRM often refers to "the use of technology to manage customer interactions and transactions" (Zoltners, Sinha, and Zoltners 2001, p. 389). Meanwhile, sales (force) automation (SFA) vendors stress that sales reps who complete routine tasks faster, easier, or better become more effective. Recent research may help to bridge the gap between CRM and SFA technologies (Widmier, Jackson, and McCabe 2002) and set up agendas for *sales technology* research (Tanner and Shipp 2005). The CRM and SFA terminology does not establish a mutually exclusive dichotomy. For example, contact management software is a common feature across both SFA and sales–CRM software packages and is intended to help sales reps manage leads, track all communications with customers, schedule follow-ups, and handle time management and planning tasks.

However, salespeople use technologies that go beyond classification as either CRM or SFA tools—including hardware and software tools that can aid their performance of sales tasks. For example, salespeople use cell phones for communications and spreadsheets for analysis, and many sales managers consider these tools critical to the firm's sales technology portfolio. However, few vendors or sales technology specialists classify cell phones or spreadsheets as either CRM or SFA technologies.

Here, we refer to sales technology as information technologies that can facilitate or enable the performance of sales tasks. As such, sales technology represents the broad range of information technologies used by salespeople, and we consider both sales–CRM and SFA tools as subsets of sales technology.

Jones, Sundaram, and Chin (2002) highlight the need for salespeople to adopt sales technology in forming customer alliances and find that personal innovativeness, attitude toward the new sales technology, and facilitating conditions influence sales technology infusion. While it is important to motivate user acceptance of information technologies (Davis 1989; Venkatesh and Davis 2000), information technology and sales technology scholarship need to get beyond the adoption issue (Ahearne, Jelinek, and Rapp 2005). One way of doing this is to properly align the CRM program with employees, processes, and technology (Zablah, Bellenger, and Johnston 2004). Consistent with these research priorities, this paper builds on previous research on information technology, sales–CRM, and sales automation to develop and test a theoretical model that demonstrates how sales managers can diagnose sales technology implementations (linking technology through behavioral selling processes to performance outcomes).

Specifically, in this study, we develop and test a normative process model with sales force data collected with the cooperation of a major CPG company. Structural equation modeling (SEM) is used to test the interrelationships among sales technology orientation, its antecedents (internal technology support, customer approval of sales technology use, and salesperson experience), and its consequences (information effectiveness, smart selling tasks, and sales performance outcomes). Because the process model is *normative,* statistically significant links in the model provide evidence of positive effects of sales technologies, whereas links that are not statistically significant illuminate areas in which the seller is not realizing expected returns. In such a case, managers should reassess the overall fit between the sales process tasks and the sales technology portfolio and, in turn, consider altering either the task or the sales technology portfolio. While this approach provides a means for diagnosing sales technology implementations, it also highlights areas where sales technology does *not* have effects (as reflected by the absence of causal paths among constructs). While the process model tested here focuses on the important new area of sales technology and is based on constructs and theory drawn from the sales management literature, the benefits of this process modeling approach are readily adapted to measures and processes specific to other information technology–performance relationships and contexts.

THEORETICAL MODEL

Figure 1 overviews a conceptual model of key antecedents and consequences of a sales technology orientation. In a field sales setting, beyond the actual information technology employed by the organization, the important effects related to successful sales technology implementations are the behaviors of the salesperson—and thus, we model key salesperson behaviors here. In this section, we provide the logic, conceptualizations, and definitions underlying this study. While much of the extant literature on sales technology focuses on simply motivating user acceptance (Ahearne, Jelinek, and Rapp 2005), our model centers on the salesperson's dispositions toward using sales technology (sales technology orientation), how sales managers can influence this important construct, and how sales technology orientation subsequently influences two key aspects of sales performance (including sales force objectives that are more internally focused within the sales organization and those that are more externally focused on buying organizations). Moreover, we propose and test the mechanisms through which those effects occur. Namely, we outline a process in which sales technology orientation improves a salesperson's ability to use information effectively, which, in turn, improves smart selling behaviors (adaptive selling and sales planning), which have been positively linked to sales performance in previous studies (Sujan, Weitz, and Kumar 1994). Our logic draws upon and integrates previous research in sales technology with perspectives from social exchange theory (Thibaut and Kelley 1959), expectancy theory (Vroom 1964), and boundary role theory (cf. Adams 1976; Organ 1971).

Sales Technology Orientation

The firm's provision of sales technologies does not ensure they will be used equally by different sales reps. It is usually at the salesperson's discretion to choose how much to rely on individual technologies. *Sales technology orientation* refers to the salesperson's propensity and analytical skills for using a portfolio of firm-provided information technologies to perform tasks relevant to the sales role.

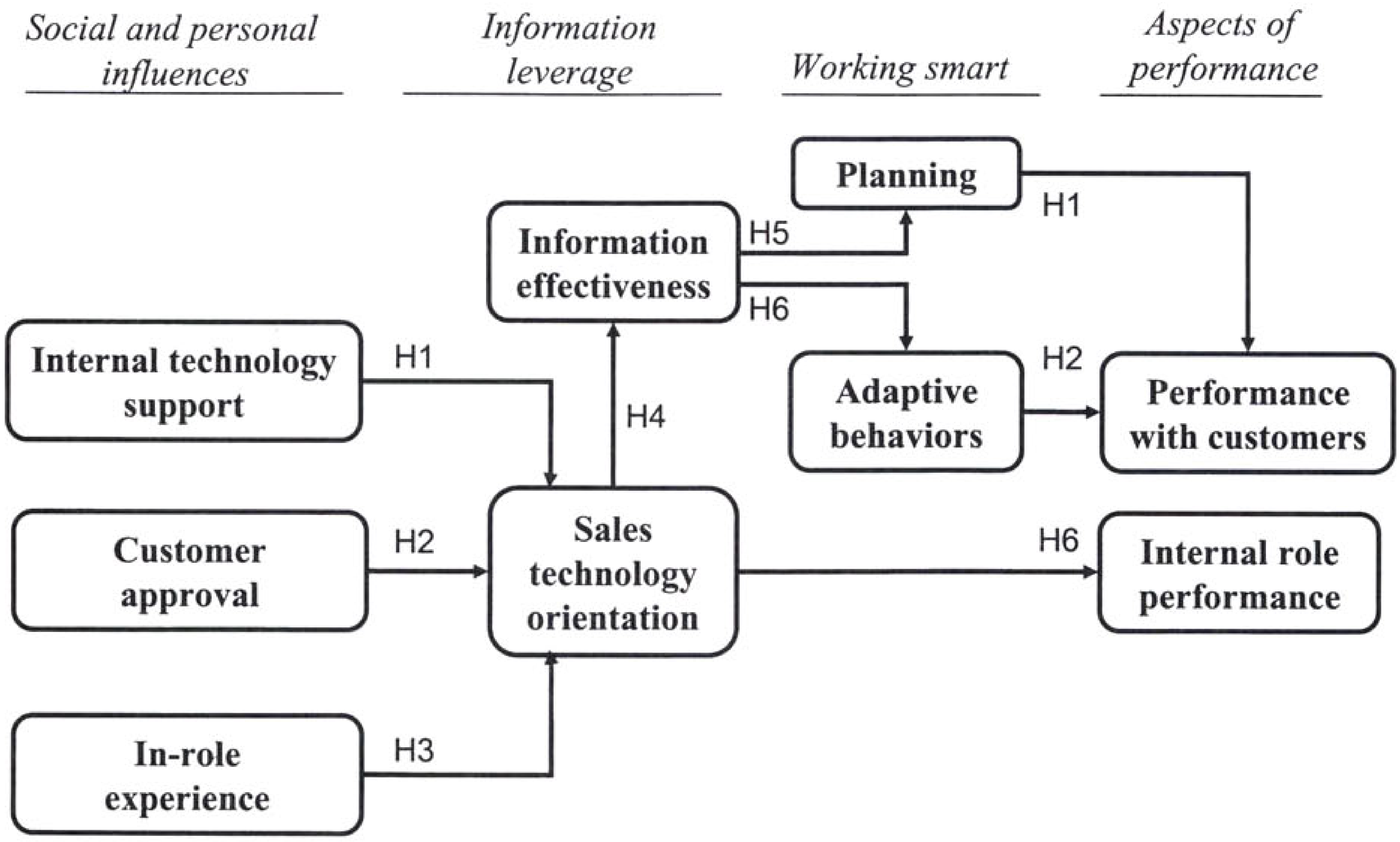
In addition to creating the right organizational culture to optimize sales performance (Oliver and Anderson 1994), sales managers influence the salesperson's orientation toward using technology and developing the necessary analytical skills to optimize its use. Specifically, social exchange theory (Thibaut and Kelley 1959) suggests that salespeople's orientation toward technology can be enhanced through actions that improve the comparison level of an existing sales technology culture to an alternative culture that more favorably supports sales technology.

Pullig, Maxham, and Hair (2002) demonstrate the importance to sales organizations of creating the right conditions for successful SFA implementations. Various factors (some controlled by the firm and some not) may influence a sales rep's technology orientation. For parsimony, our model considers three key factors suggested by existing literature as being particularly relevant to sales contexts—company internal support for sales technology, customer approval of sales technology, and experience in the sales role.

Internal technology support is the extent to which the firm provides the salesperson with resources needed to use sales technology. Social exchange theory (Thibaut and Kelley 1959) suggests that managerial actions and attitudes concerning information technology should influence salesperson behavior. Management support for sales automation plays an important role in ensuring that a sales force realizes performance returns from its investments in sales technology (Jones, Sundaram, and Chin 2002; Schillewaert et al. 2005). Such support may take various forms, including development of custom systems, training, and changes in the systems of evaluation and compensation. For example, in a field study of broker workstations, Lucas and Spitler (1999) found that management support and the nature of the task requirements were important in predicting use of technology, as users' attitudes are influenced by their colleagues' attitudes. Internal technology support thus signals the importance an organization places on sales technology.

Hypothesis 1: Internal technology support will positively affect a salesperson's technology orientation.

Figure 1
Conceptual Model of Effects of Sales Technology Orientation



Social exchange theory (Thibaut and Kelley 1959) suggests that buyer's attitudes and behaviors can influence the salesperson's orientation toward technology. Moreover, to be effective, salespeople must, in general, be responsive to customer needs and requests, including those related to information. Vroom's (1964) expectancy theory of motivation, which proposes that individuals are motivated to conduct behaviors that increase their expectancy, instrumentality, or valence for rewards, is established in the marketing and sales research (cf. Oliver 1974; Teas 1981; Walker, Churchill, and Ford 1977). *Customer approval of sales technology* represents the extent to which a customer signals expectations for technology use by the salesperson. For example, a customer who expects a salesperson to provide an analysis of both the benefits and costs of his recommendations reinforces the effective use of sales technology, whereas an "old style" buyer, who seems content with a well-organized pitch, a joke, and a slap on the back, does not. Thus, customer expectation about how the salesperson uses, analyzes, and communicates data should influence the information technologies used by sales reps (and supported by suppliers).

Hypothesis 2: Customer approval of sales technology will positively affect a salesperson's technology orientation.

The model also includes *salesperson experience* as an antecedent of sales technology orientation. Although their study's finding were not conclusive, Ko and Dennis (2004) argue that highly experienced sales reps will gain the least performance benefits from SFA system use—based on an SFA system's greater potential to provide useful knowledge to less experienced reps. Others have argued that age (which correlates with experience) has a negative effect on usage (Morris and Venkatesh 2000; Speier and Venkatesh 2002). In practice, many companies struggle with the problem that sales technologies are creating a "generation gap" among salespeople. Younger salespeople often are more "technology literate," based in part on more exposure to computing and technology during the educational process (that is, younger reps have high-technology self-efficacy). Consistent with expectancy theory (Teas 1981; Vroom 1964), we argue that salespeople with more experience learned how to be effective without the use of modern sales technologies; thus, they estimate less instrumental fit between the tasks they need to perform and the use of firm-provided sales technologies. Less instrumentality yields less motivation to adopt new technologies (Teas 1981; Vroom 1964).

Hypothesis 3: Salesperson experience will negatively affect a salesperson's technology orientation.

Information Effectiveness and Working Smart

Salespeople are knowledge workers. Our model reflects the knowledge-dependent aspects of the sales role by including *information effectiveness,* which is the value of available information for working with and gaining commitment from customers. Menon and Varadarajan (1992) highlight the vital importance of an individual's use of market information. Today, salespeople have extensive access to data (including, for example, past shipments to distributors, retail store sales, consumer buying habits, and product performance characteristics), but to be successful, they need to convert available data into information that can be used effectively toward developing and advancing recommendations and proposals that balance sales objectives with customer objectives. A central purpose of information technology is to help users convert data into effective information. When salespeople possess analytical skills and information technology know-how, they can transform the massive amounts of available data into useful and effective information for their buyers.

Hypothesis 4: More technology-oriented salespeople will use information more effectively.

The "smart selling" literature confirms the normative prescription that salespeople should plan for specific buyer interactions (Sujan, Weitz, and Kumar 1994) and tailor their behaviors to those interactions (cf. Spiro and Weitz 1990). Effective information is a necessary input for any meaningful planning process. Sales technology should facilitate or enable increased information effectiveness for a wide variety of presale planning activities. For example, spreadsheet analysis of past sales data can make the information more effective, which, in turn, improves a salesperson's planning for a sales interaction by making sales forecasts more accurate and timely.

Hypothesis 5: Information effectiveness improves a salesperson's planning.

Similarly, during a sales interaction, the effective use of information improves the salesperson's ability to anticipate and respond to buyer concerns and objections. For example, shelf-space management software (such as Apollo or Spaceman) allows a salesperson to recommend immediately a custom shelf arrangement for a new product. For example, a sales rep with a higher sales technology orientation should be able to more immediately respond to a buyer's reactions during consultation—whether conducting that consultation in person or by remote means (for example, using application-sharing software). The reason salespeople are more able to adapt is because they possess better clarity and understanding of customer information. In essence, more effective information improves the salesperson's capacity to adapt by providing patterns of meaningful insights from increasingly complex and more readily available marketplace data.

Hypothesis 6: Information effectiveness will improve the salesperson's adaptive behaviors.

Key Aspects of Sales Performance

Boundary role theory (cf. Adams 1976; Organ 1971) has become one of the most dominant theoretical frameworks used to study interorganizational relationships in the sales literature over the past three decades. While boundary role theory was developed when the prevailing view was that relationships between organizations were almost inherently adversarial—namely, organizations were forced to depend on external constituencies to both supply inputs and consume outputs (cf. Kahn et al. 1964; Katz and Kahn 1966)—it still has practical relevance for conceptualizing key aspects of salesperson performance. According to boundary role theory, to protect its members and its unique interests, an organization requires defined boundaries that are not readily permeable. In sales organizations, salespeople represent the physical manifestation of those boundaries and are called the "linking pins" between buyers and sellers (Adams 1976). As such, salespeople have long played a key role in managing relationships and information flows between selling firms and their customers. Even though firms have new capabilities, which are often driven by advances in information technology, the traditional sales role in managing buyer–seller relationships remains. Moreover, salespeople retain diverse responsibilities—some we consider more internally focused on the selling organization and others that are more externally focused on the sales organization's customers—namely, buying organizations. Accordingly, we develop and investigate relationships that drive two key aspects of sales performance—performance with customers and internal role performance. *Performance with customers* is the extent to which the salesperson cultivates relationships with the customer organization. We define performance with customers as developing an understanding of a customer's unique problems and concerns—marketing, technology, operations, or otherwise—and recommending solutions that address those concerns. For example, in a consumer market characterized by short life cycles, being first to market with a new item is often strategically important to both vendor and retailer. As such, quickly generating sales of new company products—before competitors roll out "me too" initiatives—is an important aspect of successful performance with customers.

Internal role performance refers to the salesperson's contributions on issues that are predominantly internal to the supplier's organization. This includes things such as recommending improvements in company operations and procedures, acting as a special resource to cross-functional associates, knowing the company's products, and staying abreast of the company's production schedules and technological advances.

Sujan, Weitz, and Kumar (1994) show that both planning and adaptive behaviors positively influence performance. Weitz, Sujan, and Sujan define the practice of adaptive behaviors as "the altering of sales behaviors during a customer interaction or across customer interactions based on perceived information about the nature of the selling situation" (1986, p. 175). Effective planning involves proper task prioritization, goal setting, strategic thinking, and anticipation of contingencies. By adapting the selling approach to a buyer's unique concerns or goals, salespeople should be more effective in overcoming objections and building commitment.

Hypothesis 7: Planning for sales interactions will improve performance with customers.

Hypothesis 8: Practicing adaptive behaviors will improve performance with customers.

A strong sales technology orientation can also help salespeople to be more efficient in completing nonselling administrative tasks. In fact, such efficiency is the explicit purpose of many sales automation software applications. For example, time and territory management software can improve a salesperson's ability to coordinate administrative chores. Similarly, effective use of order tracking systems, the ability to access online plant production schedules, and even effective use of e-mail can make a salesperson a better resource to associates (e.g., logistics specialists, brand managers, financial analysts, and the like).

Hypothesis 9: A stronger sales technology orientation will improve internal role performance.

It is worth noting that the absence of supporting logic and theory favors modeling other potential relationships across constructs represented as being nonsignificant (for example, experience has no direct effect on information effectiveness, sales planning, adaptive behaviors, performance with customers, or internal role performance). Explicit specification of these zero-effect hypotheses highlights the idea that the normative relationships proposed in the process model explain the whole system of direct and indirect effects related to sales technology and performance. In other words, relationships not suggested by the model should not be expected.

METHODS

Survey Sample

In selecting our sample, it was desirable to identify a firm where (1) sales technology implementation was under way, (2) use of technology and technology skills varied among salespeople, and (3) salespeople were involved in typical sales tasks (i.e., both within the selling firm and selling to customer accounts, but not to final consumers). Based on these criteria, we approached the management of a well-known CPG company and asked them to allow us to collect data from the firm's U.S. sales force and diagnose sales technology effects.

To encourage participation and improve response rates, the firm's top sales executive sent each salesperson a prenotification letter as well as a cover letter with the questionnaire, which guaranteed confidentiality to each salesperson. To further signal anonymity, we sent questionnaires to the sales rep's home office addresses and asked them to return completed questionnaires directly to the researchers' university address. Of 85 questionnaires distributed, 79 (93 percent) were returned. We dropped one respondent from the analysis because of missing data.

The host firm is a multinational Fortune 500 manufacturer and distributor of CPG with sales relationships that cut across the range of CPG business buying channels (e.g., grocery chains, wholesalers, mass merchandisers, and merchandising headquarters). Among other responsibilities, its salespeople are routinely involved in category management leadership activities for their accounts. Their use of sales technology tools includes proprietary software applications that incorporate algorithms employed by marketing scientists in the analysis of scanner data with decision inputs categorized as promotion, pricing, shelving, and distribution. The firm's ratio of revenue per salesperson is high, an indication that its salespeople are skillful.

Measures for Constructs

Prior to specifying a sample frame for the research to test the model in Figure 1, we developed an initial questionnaire and refined it based on in-depth interviews with sales executives from four different industries. Then, we narrowed our focus to identify a specific CPG firm to cooperate in the research and provide access to its sales force. The questionnaire relied on multi-item scales to develop composite measures for the constructs in the conceptual model (Figure 1). We pretested the questionnaire on sales managers within the host firm and refined the directions and wording of items as appropriate. Tables 1 and 2 present the scale items, response cues, and relevant statistics for each of the measures.

We developed the measures for sales technology orientation, information effectiveness, and other constructs in Table 1 specifically for this research. The measures in Table 2 were adapted from published scales that have been widely used by other researchers.

For example, the scale items for internal sales role performance and external performance with customers are from the inventory of sales performance items that were originally developed and evaluated for reliability and validity by Behrman and Perreault (1982; 1984). It would have been desirable to also include other reliable quantitative measures of sales performance or profit contribution provided by the company; however, management would not release incentive compensation data for individual salespeople or propriety sales

Table 1
Items and Statistics for Scales Developed in This Study: Sales Technology Orientation, Customer Approval of Sales Technology, Internal Sales Technology Support, and Information Effectiveness

Construct Name Items for Construct	Mean	Standard Deviation	GFI	IFI	CFI	Construct Reliability	Item Reliability
Sales Technology Orientation[1]	4.80	0.99	0.98	1.00	1.00	0.81	
I try to link different sales technologies so that they work together well.							0.64
I have always been fascinated by advances in technology.							0.49
Compared to others in sales, I am technology oriented.							0.48
I extensively use information technologies to perform my job.							0.45
My analytical skills explain most of my success as a salesperson.							0.24
Customer Approval of Sales Technology[1]	5.22	1.00	0.98	1.01	1.00	0.78	
The buyers that I deal with do not expect me to use technology.[2]							0.58
The buyers that I deal with are annoyed by technology.[2]							0.53
The buyers that I deal with use information technology and expect me to.							0.42
The buyers that I deal with are much more interested in personal relationships than data.[2]							0.32
My customers tend to view analysis of scanner data as completely overwhelming.[2]							0.25
Internal Sales Technology Support[1]	4.31	1.13	0.95	0.92	0.91	0.73	
My company adequately equips me with technology tools.							0.53
My company supplies all technologies that I need to perform my job.							0.45
My company adequately trains me on the use of sales technology.							0.43
I need more help with technology than I get.[2]							0.27
Information Effectiveness[3]	5.16	1.12	0.92	0.98	0.98	0.85	
Information from or about performance differences among products.							0.63
Information from or about your firm's marketing effectiveness.							0.51
Information from or about consumer buying habits for the brand or category.							0.50
Information from or about product historical profitability.							0.45
Information from or about your firm's history shipments to the customer.							0.47
Information from or about your customer's distribution costs.							0.41
Information from or about data collected in retail stores.							0.23

Notes: [1] The seven-point response cues for each item were strongly disagree (1) to strongly agree (7). [2] Responses to this item were reverse scored. [3] Respondents were directed to "please indicate how effective each of the following types of information are for earning commitment from your buyers," with seven-point response cues from totally ineffective (1) to extremely effective (7).

Table 2
Items and Statistics for Scales Adapted from Previous Studies: Planning, Adaptive Behavior, Performance with Customers, and Internal Role Performance

Construct Name / Items for Construct	Mean	Standard Deviation	GFI	IFI	CFI	Construct Reliability	Item Reliability
Planning[1]	5.72	0.76	0.96	0.99	0.99	0.78	
I am careful to work on the highest priority tasks first.							0.51
I keep good records about my account(s).							0.47
I set personal goals for each sales call.							0.41
Each week, I make a plan for what I need to do.							0.38
I do not need to develop a strategy for a customer to get the order.[2]							0.24
I think about strategies I will fall back on if problems in a sales interaction arise.							0.20
Adaptive Behavior[1]	5.38	0.92	0.94	0.87	0.86	0.69	
I treat all of the buyers pretty much the same.[2]							0.76
I feel that most buyers can be dealt with in pretty much the same manner.							0.52
I vary my sales style from situation to situation.							0.16
I can easily use a wide variety of selling approaches.							0.12
Performance with Customers[3]	5.61	0.76	0.99	1.00	1.00	0.83	
Convincing customers that I understand their unique problems and concerns.							0.80
Working out solutions to a customer's questions and objections.							0.58
Quickly generating new sales of new company products.							0.45
Listening attentively to identify and understand the real concerns of your customers.							0.42
Internal Role Performance	5.07	0.81	1.00	1.03	1.00	0.71	
Acting as a special resource to other associates who need your assistance.							0.48
Recommending on your own initiative how company operations and procedures can be improved.							0.40
Knowing the benefits and features of your company products.							0.35
Keeping abreast of all your company's production and technological development.							0.30

Notes: [1] The seven-point response cues for each item were strongly disagree (1) to strongly agree (7). [2] Responses to this item were reverse scored. [3] Respondents were directed "on each of the following items, please rate how well you have performed relative to the average salesperson in similar selling situations," with seven-point response cues from needs improvement (1) to outstanding (7).

measures on individual accounts. Beyond that, however, there were concerns about the appropriateness of available data because of differences in account/territory potential that were unrelated to the efforts of the currently assigned rep or were based on team-selling efforts. In other situations, such measures could be used (and adjusted, as appropriate, by measured variables for factors beyond the control of the salesperson). On the other hand, these are common obstacles in research on sales performance. To help address these issues, the Behrman and Perreault (1982) inventory of sales performance items has been influential in the sales research (Leigh, Pullins, and Comer 2001). Several studies have used subsets of items to represent both relevant aspects and holistic measures of sales performance (cf. Cravens et al. 1993; Fang, Evans, and Zou 2005; Fang, Palmatier, and Evans 2004; Oliver and Anderson 1994; Sujan, Weitz, and Kumar 1994). In this study, we used our construct conceptualizations and definitions to help identify items from the inventory that we felt measured the relevant aspects of performance proposed here. We then subjected those scales to extensive analysis to assess their convergent and divergent validity. As a result, we use four items each to measure the two performance constructs.

The sales planning scale draws on items developed by Sujan, Weitz, and Kumar (1994), and the items for the adaptive selling measure are from the scale developed by Spiro and Weitz (1990). For each of these scales, we used a subset of the original inventory of items. This was necessary to comply with constraints imposed by the host firm's management concerning the time required to complete the questionnaire. However, the subset of items included in the questionnaire was selected based on consistency with the original conceptualization and analysis of published correlations between individual items and the total scale.

The measure for salesperson experience is simply the respondent's report of the number of years in sales positions.

In addition to the items for the scales associated with the constructs in the model, the questionnaire included a list of different hardware and software technologies used by salespeople. The sales rep respondents were directed to indicate the extent of their reliance on each of these individual technologies using a rating scale anchored by 1= "not at all" and 7= "very heavily."

Data Analysis Methods

Consistent with the recommendations of Jöreskog and Sörbom (2001) for fitting data with our sample's characteristics, we used SEM with maximum likelihood parameter estimation to assess the psychometric properties of measures, evaluate the fit of the overall process model, and estimate parameters for the normative relationships. In many firms, the total number of sales reps (and thus the sample size for technology evaluation) is limited. However, as was done here, an effective work-around that retains the benefits of SEM with smaller numbers of observations is to first fit confirmatory factor models to assess reliability as well as convergent and discriminant validity. Estimates from the confirmatory factor analysis (CFA) are then used to scale composite scores and fix measurement error to estimate the structural model—including the relationships hypothesized in Figure 1.

There is debate in the SEM literature about the strengths and limits of different measures of fit (and no universally accepted norm). However, we relied on the comparative fit index (CFI) and incremental fit index (IFI)—statistics that are widely accepted and also robust with small samples (Fan and Wang 1998). Even though they are sample size dependent, we also report the customary chi-square statistic, degrees of freedom (df), and the goodness-of-fit index (GFI).

We supplemented our analysis using bootstrap sampling procedures to provide more parameter and standard error estimates. The general bootstrap sampling approach introduced by Efron (1979) has been widely used across various settings and has precedence in the marketing literature (cf. Bone, Sharma, and Shimp 1989; Crask and Perreault 1977). Moreover, because it has been adopted to and modified for use in SEM (cf. Bollen and Stine 1993), we will not review it in detail here. In essence, however, bootstrapping provides a nonparametric means for establishing standard errors and parameter estimates, which helps avoid concerns related to distributional assumptions needed to validate the application of asymptotically derived estimators (Efron 2000). Particular to this study, bootstrapping has been useful for obtaining robust estimations when used with nonnormal data distributions—which are common in applied research. In this study, we employ bootstrapping procedures to generate 1,000 samples used to empirically estimate the distributional properties of the hypothesized effects in the proposed structural model and to calculate potential bias in standard parameter estimates and statistical significance tests.

Evaluation of Measures

The construct reliability indices in Tables 1 and 2 are based on the shared variance between the (observed) items and the underlying latent construct; see Fornell and Larcker (1981) for computational details. The reliability estimates for all the constructs exceed 0.60, providing evidence of internal consistency (Fornell and Larcker 1981) and adequate fit (Bagozzi and Yi 1988).

To further establish the convergent validity of the eight self-report constructs, we used the guidelines advocated by Bollen (1989) and Anderson and Gerbing (1988). The *item* reliability estimates in Tables 1 and 2 are equal to the proportion of the variance in the item that is explained by its proposed latent construct; in the SEM context, this is simply the square of the standardized factor coefficient (measurement parameter). Conventionally, item reliabilities greater than 0.16 (or equivalently, parameters over 0.40) indicate that an item is internally consistent with the other items for a scale; in Tables 1 and 2, 32 of the 39 item reliabilities are over 0.25 ($\lambda > 0.50$) and only one is below 0.16. The lowest item reliability is for an item from the adaptive behavior scale. However, even for that item, the factor coefficient is 2.7 times larger than its standard error (i.e., statistically significant). Anderson and Gerbing (1988) offer the guideline that there is convergent validity among items for a construct when their estimated factor coefficients are greater than two times the associated standard error. All of these constructs and items exceed those criteria. To test the discriminant validity of the constructs, we used chi-square difference tests to compare one-factor models (e.g., covariance constrained to one) to two-factor models in a pairwise fashion across the combinations of constructs proposed here. For all comparisons, the two-factor models had better fit than their one-factor alternatives, suggesting divergence between all pairs of constructs.

Tables 1 and 2 also provide goodness-of-fit statistics for the confirmatory factor model for each construct and its associated items. The fit indices in general provide strong support for constructing scales based on these items. The lowest GFI is 0.92, which suggests a good fit of the measurement model across the analyses. Similarly, the IFI and CRI are strong, except for the adaptive behaviors construct, which indicates a marginal fit. Based on this analysis, we conclude that we have nine distinct constructs representing those proposed in the normative model.

When we compare the fit of the structural equations for our hypothesized model with the fit of an extension of that model that explicitly specifies a same-source factor (see Bagozzi 1984 for computational details), the fit is not improved (χ^2 = 10.0 with 7 df, p = 0.19). Thus, while same-source bias is always a *potential* problem with self-reports, this test provides evidence that it was not a factor in these results.

RESULTS

Model Fit and Parameter Estimates

Table 3 provides product moment correlations among all the constructs in the model. The fitting criteria for estimation of the model are based on maximizing the fit of the observed sample covariances and the implied covariance structure predicted based on the structural equations. The overall fit statistics for the structural model indicate an excellent fit (χ^2 = 25.4 with 23 df, p = 0.33; GFI = 0.93, IFI = 0.98, CFI = 0.98). Figure 2 summarizes the results of the structural model estimates. Consistent with the model specification, a single-headed arrow depicts a hypothesized relationship between constructs, and the numbers next to an arrow are the standardized parameter estimate (path coefficient) and the probability level for the test of the null hypothesis that the parameter is zero. Double-headed arrows represent the estimated (free) covariances among constructs. Omitted paths represent zero constraints.

Path coefficients for eight of the relationships specified in the model have the hypothesized sign (direction) and are statistically significant ($p < 0.05$). The path coefficient for the other relationship, between adaptive behaviors and performance with customers, is positive as hypothesized, but the probability level ($p < 0.10$) is not significant at the 0.05 level.

The path coefficients in Figure 2 consider the direct effect(s) of each independent variable. For completeness, Table 4 provides the standardized *total* effect for each independent variable on each endogenous variable. The total effect is the sum of direct and indirect effects (Bollen 1989). For example, the total effect of customer approval to use sales technology on information effectiveness is 0.15. This reflects its indirect effect through sales technology orientation and is equal to the product of the two related path coefficients (0.27 and 0.59). Thus, on average, in the host company, a customer approval rating that is one standard deviation higher stimulates a higher sales technology orientation and a 0.15 increase in information effectiveness. In general, Table 4 provides a means for relating constructs on the left side of the model in Figure 2 to those on the right side.

Sales Technology Orientation and Information Effectiveness

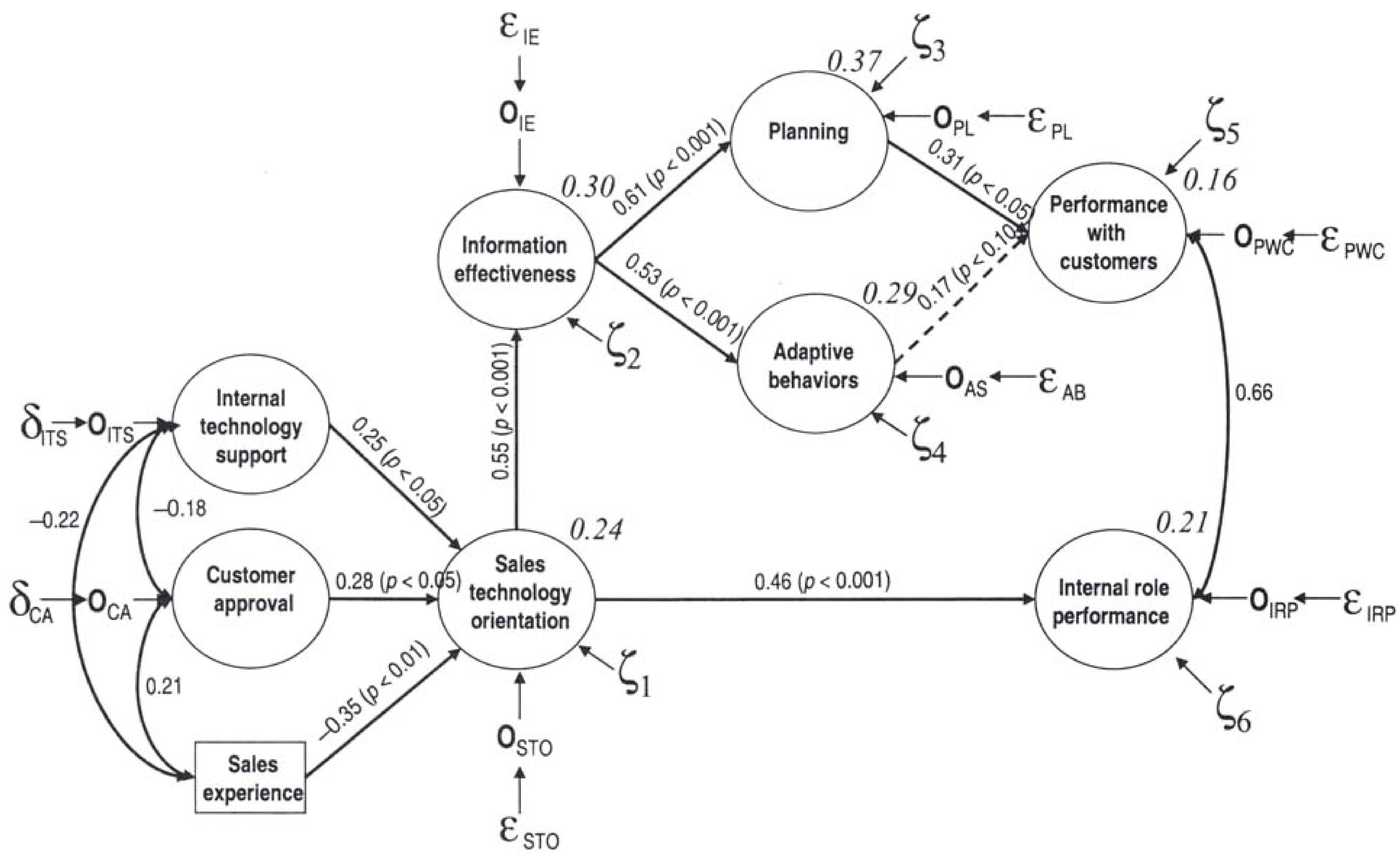
The effects of the antecedent constructs—internal technology support, customer approval of sales technology, and salesperson experience—collectively explain 24 percent of the variation in sales technology orientation. The path coefficient for customer approval of sales technology (0.28) is similar to the coefficient for internal technology support (0.25). This suggests that a salesperson's technology orientation may be influenced as much by the rep's effort to respond to buyers' approval of sales technology as it is to respond to the firm's own investments or encouragement to use technology. However, the correlation between customer approval and internal support is negative but marginally insignificant (–0.18, $p <$ 0.10) if one uses a two-tailed test. This suggests that the company's focus on technology support is not consistent with the technology needs expected from its customer base. Moreover, the –0.35 coefficient for experience in the sales role is larger in comparison and provides evidence of a statistically significant experience gap with respect to sales technology. Clearly, evaluations of technology investments that do not take into consideration individual differences among users

Table 3
Correlations Among Scales for Constructs in Model

Scales	1 Sales Technology Orientation	2 Customer Approval	3 Internal Support	4 Salesperson Experience	5 Information Effectiveness	6 Planning	7 Adaptive Behavior	8 Performance with Customers
1. Sales Technology Orientation	1.00							
2. Customer Approval of Sales Technology	0.09	1.00						
3. Internal Support for Sales Technology	0.20	–0.13	1.00					
4. Salesperson Experience	**–0.33**	0.19	–0.19	1.00				
5. Information Effectiveness	**0.40**	0.26	**0.20**	**–0.25**	1.00			
6. Planning	**0.38**	0.18	**0.24**	–0.10	**0.49**	1.00		
7. Adaptive Behavior	**0.21**	0.16	0.09	–0.04	**0.41**	**0.28**	1.00	
8. Performance with Customers	**0.23**	0.03	–0.03	0.02	0.16	**0.33**	**0.28**	1.00
9. Internal Role Performance	**0.38**	0.12	0.05	0.06	**0.23**	0.20	0.20	**0.54**

Note: Correlation coefficients greater than 0.21 result in a statistically significant *t*-test (probability less than or equal to 0.05) and are shown in boldface.

Figure 2
Summary of Structural Model Estimates



Notes: Fit statistics suggest a strong overall fit for the hypothesized model: (minimum fit function χ^2 = 25.4 (p = 0.33, df = 23), normal theory weighted least squares χ^2 = 26.01 (p = 0.30), Satorra–Bentler χ^2 = 23.58 (p = 0.43), χ^2 corrected for nonnormality = 30.23 (p = 0.14), GFI = 0.94, IFI = 0.98, CFI = 0.98, RMSEA = 0.04). Overall model fit statistics for this alternative specification (indicated by significant modification indices noted in Table 5) provide a modest improvement: (minimum fit function χ^2 = 16.9 (p = 0.72, df = 21), Satorra–Bentler χ^2 = 16.27 (p = 0.75), GFI = 0.95, IFI = 1.03, CFI = 1.03, RMSEA = 0.06). Solid lines indicate statistically significant effects supported both parametric (maximum likelihood estimation) and nonparametric (bootstrapping) estimation, based on probability values for one-tailed significance effects on path coefficients. The squared multiple correlation appears at the upper right edge of the circle for each endogenous variable.

Table 4
Standardized Total Effect (Based on Sum of Direct and Indirect Effects) for Each Independent Variable on Each Dependent Variable

	Dependent Variable for Each Path Estimated in Overall Model					
Independent Variable	**Sales Technology Orientation**	**Information Effectiveness**	**Planning**	**Adaptive Behaviors**	**Performance with Customers**	**Internal Role Performance**
Internal Sales Technology Support	0.25	0.14	0.09	0.07	0.04	0.12
Customer Approval of Sales Technology	0.28	0.15	0.09	0.08	0.04	0.13
Salesperson Experience	–0.35	–0.20	–0.12	–0.10	–0.05	–0.16
Sales Technology Orientation		0.55	0.34	0.29	0.15	0.46
Information Effectiveness			0.61	0.53	0.28	
Adaptive Behaviors					0.18	
Planning					0.30	

and buying accounts have the potential to misdiagnose why and when the investments are effective.

Sales technology orientation has a strong and statistically significant effect (0.55) on how effectively the salesperson uses information with customers. In turn, information effectiveness is positively related to the two working smart constructs. Information effectiveness explained 37 percent of the variance in planning and 29 percent of the variance in adaptive behaviors. Thus, information effectiveness did increase planning and the practice of adaptive behaviors in this sales force.

Performance

In combination, adaptive behaviors and planning explained 16 percent of the variance in performance with customers. The effect of planning is greater (a path coefficient of 0.31 versus a coefficient of 0.17 for adaptive behavior) and statistically significant. Sales technology orientation accounts for 21 percent of the variance in internal role performance.

From Table 4, note that the total effect of sales technology orientation on performance with customers is 0.15. Thus, the total effect of sales technology orientation on internal role performance (0.46) is greater than on performance with customers (0.15). So, while there are sales technology orientation returns on both performance outcomes, this suggests that the selling organization is realizing greater returns on its investments in sales technology from internal role performance outcomes, or efficiency gains in contrast to external effectiveness returns.

Taken as a whole, the results support the hypothesized indirect effects of sales technology orientation on performance with customers through information effectiveness and its subsequent effects through planning (paths H5 and H7) and adaptive behaviors (paths H6 and H8). Also, the results are consistent with the focus of past research on smart selling (H8 and H9), grounding this study within the theoretical context of previous sales management literature.

Test of Zero Constraints Across Model Constructs and Bootstrap Sampling Results

The model tests single-, double-, and triple-mediated constraints among constructs in the model. Analysis of those constraints, given an overall excellent fit for the model, provides added insights into the mechanisms through which sales technology orientation affects key aspects of performance. For example, a company can invest heavily in internal technology support but will not realize significant direct gains in internal role performance except through sales technology orientation (a single-mediated process). Furthermore, such investments would yield no return on performance with customers *except* through sales technology orientation that increases information effectiveness and planning or adaptive behaviors (a triple-mediated process). Thus, using this process, it becomes much clearer that managers must consider the tasks and processes through which sales technology tools can affect performance outcomes. If this is not done, the opportunity cost may be great.

In addition to providing alternative model specification fit statistics, Table 5 summarizes the comparisons between our bootstrapping sampling results and the parametric procedures used to obtain estimates.

Bollen (1989, pp. 267–268) notes that no hard fast rule for sample size exists, but it is desirable to have at least several cases per free parameter estimated. Similarly, Bentler and Chou (1988, p. 172) refer to their own widely used 5:1 ratio for sample size to number of free parameters estimated as an "oversimplified guideline" and not an absolute. Nonetheless, many SEM researchers use the 5:1 ratio of sample size to parameter estimates as an "absolute" guideline, but there really is no absolute minimum sample size or even an absolute minimum ratio.

We fit the proposed model to 1,000 bootstrap samples and used the estimates from those fittings to develop robust standard error estimates. Bootstrap estimates are provided with the estimated percentage of bias in the maximum likelihood parameter estimates and standard errors. For all hypotheses but one, the results of the bootstrap provide incremental evidence that supports the results of the maximum likelihood estimates (e.g., seven of the nine hypotheses are supported, one is rejected, and one is only "marginally" supported). By dividing the lowest magnitude parameter estimate (either maximum likelihood or bootstrap) by the highest magnitude standard error (which is always the bootstrap standard error), we form a statistic that can be compared to *t*-distribution tables ($\alpha = 0.05$) for statistical significance testing. The bootstrap suggests the relationship between the firm's support for information technology and sales technology orientation is weak (only marginally supported by the data).

In SEM, each endogenous variable has a structural error associated with its prediction by other variables in the model. The alternative model modifications represent inclusion of statistically significant (nonzero) path estimates that are hypothesized in the proposed model to be nonsignificant. Sörbom (1989) proposed the use and interpretation of modification indices obtained when fitting the proposed structural model as a means for developing and testing alternative model specifications. Only two of the 45 zero-constrained relationships (18 in the β matrix of η to η effects, 15 in the γ matrix of ξ to η effects, and 12 in the structural error term covariance matrix, ψ) had significant modification indices, suggesting a better model fit could be obtained by freeing these elements. Specifically, modification indices suggested two sequenced changes to the proposed structural model: (1) freeing

Table 5
Summary of Structural Model and Bootstrap Results

Dependent Variable Independent Variable	Hypothesized Effect[1]	Full Information Maximum Likelihood Unstandardized Parameter Estimate (standard error)	*t*-Value	Full Information Maximum Likelihood Standardized Parameter Estimate	*p*-Value	Bootstrap Mean Unstandardized Parameter Estimate (standard error)	Bootstrap Estimated Parameter and (standard error) Bias (in percent)	Direct Effect Hypothesis Supported (α = 0.05)?[2]
Performance with Customers								
Planning	+	0.30 (0.13)	2.36	0.31	< 0.05	0.29 (0.15)	3.3 (–7.1)	Yes
Adaptive Behaviors	+	0.14 (0.14)	1.01	0.19	< 0.10	0.17 (0.15)	–21.4 (–1.6)	No
Internal Role Performance								
Sales Technology Orientation	+	0.37 (0.09)	3.93	0.59	< 0.001	0.38 (0.11)	2.7 (22.2)	Yes
Planning								
Information Effectiveness	+	0.42 (0.10)	4.22	0.61	< 0.001	0.42 (0.11)	0 (–10.0)	Yes
Adaptive Behaviors								
Information Effectiveness	+	0.44 (0.11)	4.04	0.48	< 0.001	0.45 (0.12)	–2.3 (–9.1)	Yes
Information Effectiveness								
Sales Technology Orientation	+	0.62 (0.14)	4.51	0.59	< 0.001	0.63 (0.15)	1.6 (–7.1)	Yes
Sales Technology Orientation								
Internal Technology Support	+	0.22 (0.12)	1.85	0.27	< 0.05	0.22 (0.14)	0 (–16.7)	Marginal
Customer Approval	+	0.27 (0.13)	2.07	0.27	< 0.01	0.27 (0.15)	0 (–15.4)	Yes
Salesperson Experience	–	–0.25 (0.08)	–2.98	–0.35	< 0.001	–0.24 (0.09)	4 (–12.5)	Yes

Alternate Model Specifications[3]	Modification Index	Zero-Constraint Hypothesis Supported?
Structural Error Term Covariances		
Sales Technology Orientation and Information Effectiveness	26.9	No
Information Effectiveness and Sales Planning	15.1	No
Other 43 Zero-Constrained Hypotheses in β, γ, and ψ Matrices	< 5.0	Yes

Notes: Fit statistics suggest a strong overall fit for the hypothesized model: (minimum fit function $\chi^2 = 25.4$ ($p = 0.33$, df = 23), normal theory weighted least squares $\chi^2 = 26.01$ ($p = 0.30$), Satorra–Bentler $\chi^2 = 23.58$ ($p = 0.43$), χ^2 corrected for nonnormality = 30.23 ($p = 0.14$), GFI = 0.94, IFI = 0.98, CFI = 0.98, RMSEA = 0.04). [1] The hypothesized effects summarized here include only the direct effects conceptualized herein and shown in Figure 1. The alpha level chosen for significance testing was 0.05 and, in the most conservative test, we would choose the parameter estimate with the lowest magnitude and divide that by the bootstrap standard error estimate to construct t-values for testing. The hypothesized structural model constrains to zero all other potential effects among variables whose path coefficient is not freely estimated. See Table 4 for a summary of total effects (direct and indirect). [2] The overall model fit and modifications indices (Sörbom 1989) were used to test all nonzero relationships, including, for example, the double- and triple-mediated processes through which the three exogenous variables (internal technology support, customer approval, and in-role expertise) influence the two aspects of performance (performance with customers and internal role performance). All hypothesized zero-constrained paths (constrained feedback loops) in the original model were supported (i.e., none have effects that statistically differ significantly from zero). Exogenous variables were allowed to covary, and the three covariance estimates obtained from the analysis were –0.18 between internal support and customer approval, –0.22 between internal support and salesperson experience, and 0.21 between customer approval and salesperson experience. [3] The alternative model modifications represent inclusion of statistically significant (nonzero) path estimates that are hypothesized in the proposed model to be nonsignificant. Sörbom (1989) proposed the use and interpretation of modification indices obtained when fitting the proposed structural model as a means for developing and testing alternative model specifications. Two of the 45 zero-constrained relationships (18 in the β matrix of η to η effects, 15 in the γ matrix of ξ to η effects, and 12 in the ψ matrix of structural error term covariances) had significant modification indices, suggesting a better model fit could be obtained by freeing these elements. The overall model fit statistics for this alternative specification provide a modest improvement: minimum fit function $\chi^2 = 16.9$ ($p = 0.72$, df = 21), Satorra–Bentler $\chi^2 = 16.27$ ($p = 0.75$), GFI = 0.95, IFI = 1.03, CFI = 1.03, RMSEA = 0.06).

the structural error covariances for the error terms associated with modeling sales technology orientation and information effectiveness (modification index = 25.9) and (2) freeing the structural error terms associated with the information effectiveness and sales planning constructs (modification index = 15.1). The overall model fit statistics for this alternative specification provide a modest improvement: minimum fit function $\chi^2 = 16.9$ ($p = 0.72$, df = 21), Satorra–Bentler $\chi^2 = 16.27$ ($p = 0.75$), GFI = 0.95, IFI = 1.03, CFI = 1.03, root mean square error of approximation [RMSEA] = 0.06.

DISCUSSION AND CONCLUSIONS

The results of the study presented here are generally consistent with the parsimonious model proposed and, at the same time, provide diagnostic insights about the role of sales technology. The structural model reveals that the data are consistent with this conceptualization. The model explains 16 percent of the variance in performance with customers and 21 percent of the variation in internal role performance. There is, of course, unexplained variance from other factors, such as effort, but these results compare favorably with past research in sales performance. For example, in their meta-analysis of 75 years of sales performance research, Churchill et al. (1985) note that, on average, no single variable accounts for more than 10 percent of the variation in salesperson performance. Yet the two working smart predictors explain 16 percent of the variance in performance, while customer and sales technology orientation alone explains 21 percent of the variation in internal role performance.

From a statistical theory perspective, this study poses two primary limitations—within-firm design and sample size. The use of a within-firm design warrants caution concerning the applicability of our results across a broad spectrum of firms—although generalizations to other firms within the CPG industry are less remote. On the other hand, these limitations provide an opportunity to demonstrate an appropriate application of the SEM process recommended here within a small sample context. Because many sales organizations have less than 100 employees, this is a reality that many sales managers would face when carrying out this approach. However, SEM methods are used in academic research for similarly sized samples. For example, a recent content analysis of over 500 publications of SEM studies in psychology journals points out that about one-fifth had sample sizes smaller than 100 (MacCallum and Austin 2000). Thus, our application in this sample size is not unique (although our work goes well beyond the norm in providing extensive bootstrapping results across various estimators to demonstrate the stability of the parameter estimates). This added step adds more credibility and confidence toward the internal validity of our study—and would do the same for others implementing this approach.

It is important to note that one of our objectives was not only to propose the means for managers to diagnose sales technology implementations but also to do so in a manner that provides a tractable within-firm diagnostic tool. To be a tractable within-firm diagnostic tool, the data needed for modeling the relationships needed to be accessible to the sales managers—and a survey of their own salespeople meets that criterion. In sum, the methods used in this study are tractable to within-firm investigations, but they are also analytically sophisticated, and care should be taken when interpreting these results—particularly with regard to inferences concerning cause and effects.

At the same time, the results in Table 4 highlight the fact that the total effect of sales technology orientation on internal role performance here is 0.46, as contrasted with a total effect of 0.15 for performance with customers. From a diagnostic standpoint, this implies that in this company, sales reps with an inclination and the analytical skills for applying information technologies to their sales tasks are having more effect on internal processes and operations than they are in resolving customer problems and concerns. In the modern era of relationship marketing, that is a finding worthy of management's consideration. Specifically, from a normative standpoint, there is an opportunity for our host firm to put more emphasis on technologies that improve performance with customers.

There is not evidence from this study on which to argue that this pattern would apply across other CPG supply situations (i.e., with other suppliers), but we speculate that this is the case. Case studies in the popular press tend to emphasize sales automation applications, the focus of which tends to be on cutting sales force costs or making more efficient the flow of information needed by the supplier company. Further, these applications focus on existing tasks rather than on enabling tasks that previously were not performed (or performed well). On the other hand, the ability and effort required of a sales rep in applying information technology to come up with integrative, win-win solutions for both the company and the retailer are less structured and tend to require more adaptive, custom efforts. Yet it is this type of application where sales technology may have a greater impact on the revenue-generating side of category management efforts.

The process modeling approach presented here relies on estimated effects rather than on direct user evaluation or judgments of which sales technologies are most useful in completing different sales tasks. It is not our intent to suggest that user evaluations of information technologies are not potentially useful but, rather, that estimation of the impact of technologies via a process model provides complementary information. To elaborate on this difference, we asked respondents to rate their reliance on various sales technologies, calculated the mean and standard deviation of the respondents' ratings, and correlated the reliance ratings with the constructs in our proposed model. In lieu of providing all descriptive data here, to illustrate our point, we isolate one of those technologies—shelf-space management software. From a diagnostic standpoint, this was one of the least frequently used applications, yet it also had the highest bivariate correlation with both internal role performance and performance with customers. Although reliance on this sales technology shows a relationship to process and performance outcomes, it is not correlated with internal support. This finding suggests that the process modeling approach may add incremental information beyond user evaluations that could improve management decision making, although further research is needed.

The behavioral process modeling approach used in this study offers a flexible method for diagnostic modeling of the technology-to-performance relationship and how it works through behavioral mechanisms. To apply the approach to diagnose sales technology implementations, managers can develop normative models of their sales technology processes, beginning with desirable outcomes, identifying behavioral mechanisms that affect those outcomes, and then mapping out antecedent influences of those outcomes. This approach can be used across a wide variety of settings through which technology is thought to affect behavioral processes. While our model specification is parsimonious and focuses on information effectiveness and smart selling tasks, in other contexts, the model specification could be expanded to include other relevant antecedents, technologies, process tasks, and criterion variables.

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