

Technology use on the front line: how information technology enhances individual performance

Suresh Sundaram · Andrew Schwarz · Eli Jones ·
Wynne W. Chin

Received: 11 July 2006 / Accepted: 26 September 2006 / Published online: 3 February 2007
© Academy of Marketing Science 2007

Abstract This study explores and tests a new model that links different types of technology usage to individual-level outcomes. The primary objective of this study is to examine the effects of efficient use (routinization) and effective use (infusion) along with the traditional measure of usage—namely, frequency of use—on two dimensions of individual-level outcomes: information technology-enabled administrative performance and information technology-enabled salesperson performance. To maintain

consistency with the existing literature, the authors examine the effects of predeployment attitude toward or acceptance of technology and pre-deployment intended use of technology. The authors discuss managerial implications and provide directions for future research.

Keywords Technology · CRM · Customer relationship management · Sales force automation · SFA · Salesperson performance · Individual performance · Sales · Salespeople sales management · PLS · Partial least squares · SEM · Structural equations modeling

Authors are listed in reverse alphabetical order and contributed equally. The authors thank the editor; four anonymous *JAMS* reviewers; and Carl Herman, a former Siebel executive and current Director of Partner Relations for the Sales Excellence Institute, for their helpful comments on a previous draft of this manuscript.

S. Sundaram
Department of Marketing, Law and Social Responsibility,
Loyola College in Maryland Sellinger School of Business,
4501 North Charles Street,
Baltimore, MD 21210, USA
e-mail: ssuresh@loyola.edu

A. Schwarz
Department of Information Systems and Decision Sciences,
E. J. Ourso College of Business Administration,
Louisiana State University,
Baton Rouge, LA 70803, USA
e-mail: aschwarz@lsu.edu

E. Jones (✉)
Department of Marketing and Entrepreneurship,
Bauer College of Business,
Sales Excellence Institute University of Houston,
Houston, TX 77204-6021, USA
e-mail: eli-jones@uh.edu

W. W. Chin
Department of Decision and Information Sciences,
Bauer College of Business, University of Houston,
Houston, TX 77204-6021, USA
e-mail: wchin@uh.edu

In recent years, strategic issues involving frontline customer contact personnel and technology have come to the forefront of trade journals and academic research (Honeycutt, T. Thelen, S. T. Thelen, & Hodge, 2005; Rangarajan, Jones, & Chin, 2005). There is growing interest in identifying the appropriate tools for sales personnel that improve sales force productivity (Morgan & Inks, 2001), particularly sales force automation (SFA) and customer relationship management (CRM) tools. These tools are designed to automate the collection and assimilation of customer data and the distribution of market intelligence to frontline sales and customer service personnel (Morgan & Inks, 2001). Tools such as Salesforce.com and Siebel SFA enable salespeople to manage their contacts, create effective sales presentations, and submit call reports and sales forecasts, among other tasks (Gohmann, Barker, Faulds, & Guan, 2005).

A typical organization spends an estimated \$5,000 to \$15,000 per salesperson to equip him or her with the appropriate SFA/CRM technology (Erffmeyer & Johnson, 2001). However, despite substantial investments in technology, companies continue to experience pain (e.g., lost sales) rather than profit (Thetgyi, 2000). Several studies

conclude that 55 to 80% of all SFA projects are unsuccessful because frontline personnel are not fully using these technologies (Rivers & Dart, 1999). In addition, other studies speculate that despite substantial investments in technology for the sales force, there has been no noticeable increase in productivity at the organization level (Galvin & Berg, 2003), nor has there been any impact on bottom-line performance (Speier & Venkatesh, 2002). The studies in this area of investigation have generated mixed results (Ahearne, Srinivasan, & Weinstein, 2004; Avlonitis & Panagopoulos, 2005), suggesting a need to understand better the mechanisms through which the use of these tools leads to improved information technology (IT)-enabled performance.

This study explores how the use of SFA/CRM tools can lead to improved IT-enabled salesperson productivity. Overall, we propose a model that describes the relationship between pre-deployment intentions and attitudes to specific types of systems usage (Fig. 1). The basic premise of the model is that integrating SFA/CRM technology into the sales function positively contributes to IT-enabled administrative and sales performance.

Figure 1 outlines the temporal order of progression from the standpoint of pre- and post-technology deployment. Pre-deployment captures a person's attitude toward technology and his or her intention to use it before receiving the technology. Because attitude and intention are rooted in technology acceptance theories, we expect both to predict the person's actual IT usage. We elaborate on the types of usage in the next section. Finally, IT-enabled performance will result from actual use at both the administrative level and the salesperson level.

The rest of the paper is organized as follows: first, we outline the theoretical framework for our model. Second, we discuss the elements of the framework and how they are

related to one another, and then we present empirical support for our exploratory study. Finally, we discuss the results and offer conclusions.

Literature review

We propose that understanding the relationship between technology use and outcomes is fundamental to determining how IT leads to desirable results. To achieve IT-based productivity gains, the technology must be used fully (Venkatesh & Davis, 2000). However, we believe that different types of technology use lead to the desirable outcomes. Thus, the nomological framework that we propose requires a theoretical understanding of two domains of literature: information systems (IS)/IT use and salesperson performance.

In the IS/IT literature, a variety of models have been advanced to explain IT usage (Venkatesh, Morris, G. B. Davis, & F. Davis, 2003). Of these, the most widely tested model is the technology acceptance model (TAM), which Davis, Bagozzi, and Warshaw (1989) proposed. However, all these models, including the TAM, aim to understand how people accept IT but stop short of addressing how the use of IT leads to an increase in performance.

Ahearne et al. (2004) suggested that beyond a certain point, SFA/CRM technology use can have a disabling effect on salesperson performance. In contrast, Ko and Dennis (2004) found that SFA use is directly proportional to performance and that salespeople with high technological expertise receive the greatest benefit. However, Ko and Dennis did not find a difference in the benefits received between experienced and new salespeople. These findings emphasize the advantage of technological expertise over

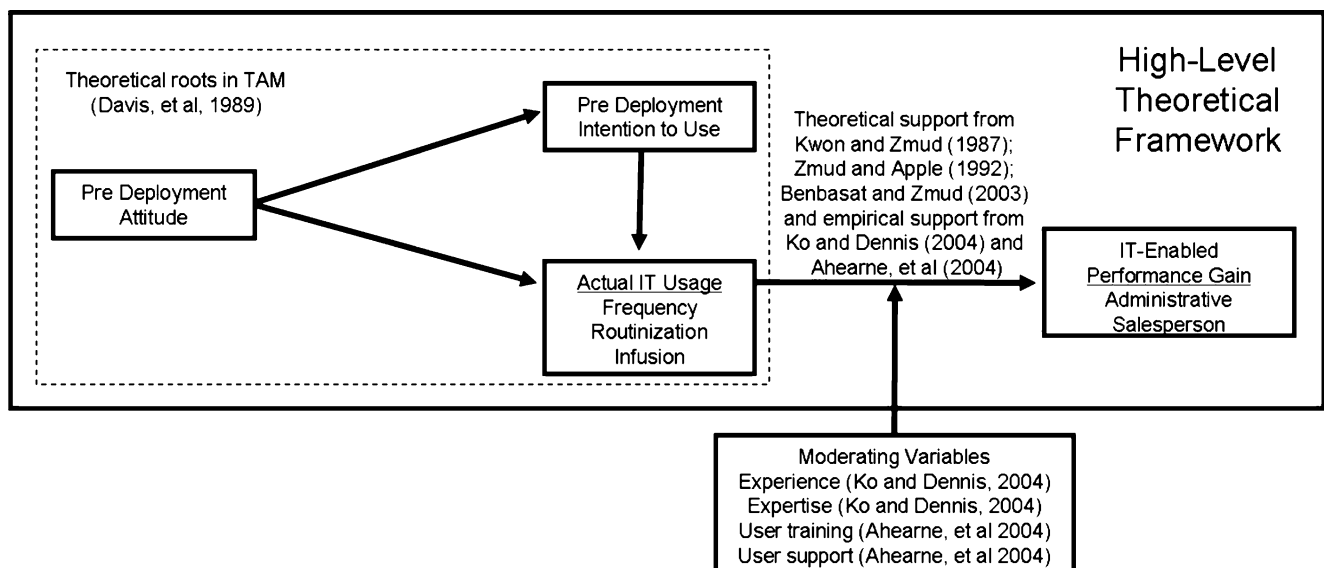


Figure 1 Theoretical model.

sales experience in terms of achieving the maximum benefit of sales technology. Similarly, Ahearne, Jelinek, and Rapp (2005) found that the use of SFA enhances salesperson efficiency and effectiveness only under conditions of adequate user support and training.

Connecting the different types of usage to their corresponding effects on performance has occurred at the theoretical level. Kwon and Zmud (1987, p. 232) stated that though “no clear precedence relationship exists among use, performance, and satisfaction, it seems reasonable to suggest that all are preceded by acceptance in at least two cases: when use is voluntary, and when performance is dependent on committed, rather than vapid use.” Although it is beyond the scope of the current study to examine the process of acceptance, Kwon and Zmud support our argument that performance is dependent on use and that there is a distinction between “committed” and “vapid” use. Although Kwon and Zmud did not elaborate further on the different types of use, they suggested the notion of strong versus weak usage.

At the organizational level, Zmud and Apple (1992, p. 148) argued that “the extent to which the expected benefits of an innovation...are realized is largely reflected in the success by which an innovation has been incorporated within the organization’s operational and/or managerial work system.” Benbasat and Zmud (2003, p. 186) argued for the theoretical link and suggested that a core set of principles for the IT discipline should be to examine the “consequence of use, the impacts (direct and indirect, intended and unintended) of these artifacts on the humans who directly (and indirectly) interact with them, structures and contexts within which they are embedded, and associated collectives (groups, work units, organizations).” Our core thesis that there is a relationship between usage and performance has been historically supported in the IT literature as a sequential process from attitudes to behaviors to performance outcomes.

Therefore, on the basis of the theory of planned behavior/theory of reasoned action, which is the foundation for TAM, we suggest that a person’s attitude toward the technology before deployment influences his or her intention to use the technology after deployment. Human action is then an outcome of a combination of the intention and the pre-deployment attitude. Thus, we examine pre-deployment attitudes and the behavioral outcomes of those attitudes leading to performance outcomes.

Pre-deployment attitudes and the outcome of attitudes

The IS/IT literature has examined the effect of a person’s prior attitude toward a new technology, its effect on intended use, and its effect on performance (Goodhue & Thompson, 1995). Avlonitis and Panagopoulos (2005)

demonstrated that the perceived usefulness of a CRM system results in improved salesperson performance. To extend the work of Avlonitis and Panagopoulos, and in line with the IS/IT literature, we hypothesize that the more positive a person’s attitude toward technology usage pre-deployment, the greater is his or her intention to use the technology. Furthermore, a person’s pre-deployment attitude toward technology should positively affect his or her actual IT usage.

IT usage: the behavioral outcome

The central premise of our investigation is that managers may be better able to predict the impact of SFA/CRM technology on salesperson performance if they focus on understanding the types of use beyond the traditional indicator, extent of use. We posit that the extent to which the performance benefits of an innovation are realized is largely reflected in the level at which the person has incorporated innovation within his or her work structure. Furthermore, the benefits are dependent on the optimized symbiosis between the technology and the person, to the point at which the relationship can realize its fullest potential. Thus, the act of incorporation for a person is the process of use during which his or her routines may need to be altered and the technology is used to its fullest potential. We suggest that there are three types of use: the degree to which (1) the person uses the technology (extent or frequency of use), (2) the person adapts to IT usage or incorporates it into his or her routine work pattern (routinization), and (3) the person maximizes the potential of the technology (infusion). To our knowledge, this three-part distinction for types of use has not been explored at the individual level.

At the organizational level, researchers have studied the extent of infusion and routinization when analyzing the diffusion of innovations within organizations (Cooper & Zmud, 1990; Zmud & Apple, 1992). We acknowledge that IS/IT researchers have used other measures, such as the depth and breadth of usage and alternative conceptualizations of use, beyond that which we describe. However, in each of these cases, the theoretical underpinnings were not developed for linking technology use to individual performance.

In most of the studies we discuss herein, metrics designed to examine usage have focused on the extent of use, typically measured as the frequency or amount of time that a person uses technology. Likewise, this is the measure that has been used in the few studies that have attempted to examine the relationship between SFA technology usage and performance (Ahearne et al., 2004; Ahearne et al., 2005; Ko & Dennis, 2004).

Note that though a person may make considerable use of a given technology, he or she might not necessarily

demonstrate an increase in performance. However, it is significant that though efficient use is important, so is effective use. We suggest that the notion of effective use is captured in the concept of infusion, or the extent to which a salesperson fully uses the technology to enhance productivity (Jones, Sundaram, & Chin, 2002). Routinization refers to the integration of the technology into work patterns and does not necessarily mean that a person uses the full degree of potential offered by the system. Our primary concern is the cognitive structures being enacted by the use of the technology and the resulting behavioral (productivity) outcomes. As such, we exclude any exploration of the user's dependence on the technology.

We suggest that there is an interrelationship among frequency, infusion, and routinization. However, to achieve both infusion and routinization, a person must (1) formulate an intention to use the technology and then (2) actually use it. The increased usage then creates an opportunity for the technology to be infused and routinized. Thus, we suggest that the extent of use predicts both infusion and routinization. Theoretically, we expect that the more a person engages in a technology, the more likely he or she will be to integrate the technology and, thus, to use the technology to enhance his or her own productivity.

In the process model of IT implementation, Cooper and Zmud (1990) proposed that routinization precedes infusion. Therefore, adapting this to the individual level, we propose that obtaining higher infusion levels may require behavioral changes to enable a stable working-level set of routines (i.e., infusion is preceded by routinization).

Nonetheless, the concepts of frequency, routinization, and infusion are only determined post hoc, that is, after the system has been deployed and people have begun using it. There is a temporal distinction between these measures: frequency, infusion, and routinization occur after deployment, whereas expected extent of use occurs before deployment. Therefore, we suggest that the extent to which a user projects that he or she will use the system before deployment will influence usage frequency, the degree to which usage frequency is routinized, and the extent of infusion. On the basis of this discussion, we hypothesize that the stronger the intention to use SFA technology before deployment, the greater is the use of the technology after deployment.

Performance outcomes: outcomes of usage

Traditionally, both in academia and in industry, total sales volume has served as a primary indicator of salesperson performance (Morris, Davis, Allen, Avila, & Chapman, 1991). However, scholars have attempted to show that salesperson performance is multidimensional (Barker, 1999). Thus, there is considerable value in exploring the

effects of technology usage on other dimensions of performance rather than simply focusing on quantitative measures of salesperson performance.

Barker (1999) posited that nonselling performance and selling behavior performance lead to sales force outcome performance. Furthermore, Barker defined nonselling performance as activities that are sales-related administrative activities, and he argued that sales force selling behavior is composed of selling capability and technical knowledge. Oliver and Anderson (1994) provided further support for this notion of multidimensionality of salesperson performance. Such a view is fairly consistent with the view that performance has two dimensions (see Behrman & Perreault, 1984): the achievement of sales objectives and the performance of administrative tasks. Consistent with this perspective, we specifically define these two outcomes as follows:

- “IT-enabled administrative performance” is a measure of the extent to which the technology affects the quality of the salesperson's call planning and time and expense management. These tasks are critical to the selling function but are different from typical measures of sales performance.
- “IT-enabled salesperson performance” is the extent to which the technology affects the quality of the salesperson's ability to produce key sales results.

Relationship between types of technology use and salesperson performance dimensions

Researchers have argued that low usage of installed systems is a major factor underlying the “productivity paradox,” resulting in lackluster returns on organizational investments in IT (Venkatesh & Davis, 2000). Thus, it can be concluded that frequency of use of the technology likely drives both dimensions of salesperson performance. However, we include the caveat that such use represents only a necessary, but not sufficient, criterion for performance. It is important to note that the mediating role of the manner of use is equally vital. In other words, how the technology is used mediates the relationship between the extent of use and performance. A salesperson who integrates SFA/CRM into his or her work routine or infuses the technology can leverage the technology with minimum cognitive expense, thus maximizing the ratio of output to input for a high degree of sales force performance. Therefore, we hypothesize that the greater the use of SFA technology after deployment (“use” is defined as frequency, routinization, and infusion), the greater is the impact of the technology on productivity (administrative and salesperson).

Thus, we examine the effects of pre-deployment attitude on pre-deployment intention to use, which in turn predicts actual IT usage (i.e., frequency, infusion, and routinization).

Furthermore, we test how the types of usage predict IT-enabled performance (including both administrative and salesperson).

Materials and methods

Measurement

We summarize the constructs and the respective definitions used to develop the study measures in the [Appendix](#). To measure the constructs, we generated items that corresponded to the definitions and reflected the proposed theoretical model. Jones et al. (2002) developed the scale for infusion, and we developed the measure of routinization for this study. We outline both of these in the [Appendix](#).

Sample

We collected data for this study by surveying salespeople (from locations across the United States) employed by a large US-based insurance company. Recently, there has been a call for the use of independent agents whose use of technology is not within their employers' control (Speier & Venkatesh, 2002). Following this advice, we selected the company because its sales agents were remunerated entirely on sales commissions and use of the SFA system was voluntary. The salespeople purchased the preconfigured laptop and specialized software that helped build presentations, share information, compute annuities, and check order status and commissions. The company provided us with a list of agents who were due to be offered the SFA system for voluntary use. We then mailed the questionnaires directly to the agents, along with a letter that requested their participation in the study. To ensure high participation levels, all our mailings were preceded (with a 1-week lead time) by a personal letter from the company's vice president of sales that encouraged the agents to participate in the study. A copy of the letter was also included in our mailings to serve as a reminder.

Data collection

We collected data in two waves. The first wave of data collection was mailed out approximately 2 weeks before the scheduled rollout of the company's SFA system in each region. A total of 305 questionnaires were mailed to the sales agents in the first wave. We received 164 usable responses during the first wave, for a response rate of 53.8%. We conducted the second wave to obtain self-reports of actual usage behavior 6 months after the conclusion of the first wave of data collection. The questionnaires were mailed to the 164 agents who

responded to the first wave, and we received 85 usable responses, for a response rate of 51.8%. Thus, 27.9% of the original sample completed both waves of the survey.

The first questionnaire included measures for all the nonbehavioral variables, and the second questionnaire elicited responses pertaining to the agents' self-reported usage of the SFA system and their current attitudes toward the SFA/CRM system. The first wave of data collection included the agents' projected intention to use the system, and the second wave included the measures for the remainder of the items. The two waves were separated so that the self-reported behavior would be less likely to be contaminated by responses to the nonbehavioral variables (see Shimp & Kavas, 1984).

Analysis

We analyzed the data using structural equation modeling. Given (1) our small sample size for the second round of data (85 respondents), (2) the mixed model that we tested (i.e., IT-enabled administrative performance and IT-enabled salesperson performance are formative indicators, and the other constructs are reflective), and (3) the presence of identification constraints (due to the formative indicators), we were unable to use a covariance-based approach (MacCallum & Browne, 1993) and thus selected the partial least squares (PLS) approach, specifically PLS-Graph (version 3.00, build 1126) software.¹

The choice of a PLS-based approach was attributed to our power analysis (guided by MacCallum, Browne, & Sugawara, (1996)), which suggested that for a covariance-based approach, we needed a minimum of 93 cases to obtain a standard 0.80 power level, given our model at the 0.05 alpha level and a sample size of 127 for an alpha level of 0.01. Although Anderson and Gerbing (1988) and Gerbing and Anderson (1985) suggested a two-step process and analysis of sample size for covariance-based approaches, we were unable to use this approach given our data size and measurement model.

Results

Measurement model results

The first step in a PLS analysis is the analysis of the measurement (or outer) model. First, we examined the adequacy of the measures to ensure that the items measured the constructs as they were designed. All the elements met

¹ Under the umbrella of structural equation modeling are two main approaches: covariance-based (which is found in software such as LISREL, AMOS, and EQS) and PLS (which is found in software such as PLS-Graph).

Table 1 Loadings and cross-loadings

	Projected extent of use	T1 attitude	Usage frequency	Routinization	Infusion	IT-enabled administrative performance	IT-enabled salesperson performance
PU1	0.905	0.478	0.444	0.423	0.33	0.295	0.147
PU2	0.938	0.702	0.516	0.437	0.334	0.334	0.182
ATT1	0.627	0.975	0.483	0.457	0.359	0.335	0.211
ATT2	0.664	0.956	0.542	0.484	0.371	0.312	0.192
ATT3	0.526	0.871	0.433	0.375	0.355	0.344	0.171
UF1	0.502	0.439	0.955	0.758	0.543	0.386	0.207
UF2	0.504	0.558	0.964	0.765	0.603	0.512	0.31
ROUT1	0.456	0.47	0.767	0.976	0.741	0.609	0.327
ROUT2	0.453	0.448	0.781	0.989	0.735	0.604	0.387
ROUT3	0.465	0.472	0.789	0.980	0.737	0.589	0.364
INFU1	0.39	0.418	0.623	0.776	0.955	0.618	0.461
INFU2	0.381	0.44	0.604	0.768	0.957	0.6	0.421
INFU3	0.023	0.077	0.193	0.315	0.663	0.247	0.328
INFU4	0.344	0.298	0.548	0.642	0.893	0.466	0.311
ADMIN1	0.297	0.317	0.462	0.577	0.47	0.883	0.426
ADMIN2	0.358	0.374	0.438	0.603	0.571	0.926	0.432
ADMIN3	0.236	0.222	0.332	0.415	0.475	0.805	0.46
SALES1	0.076	0.206	0.087	0.236	0.246	0.339	0.684
SALES2	0.103	0.181	0.272	0.298	0.286	0.386	0.871
SALES3	0.227	0.259	0.371	0.449	0.55	0.519	0.892
SALES4	0.096	0.074	0.134	0.19	0.218	0.361	0.879

NOTE: Numbers in bold are loadings (correlations) of indicators to their own construct; other numbers are cross-loadings. For cross-loadings, we calculated a factor score for each construct on the basis of the weighted sum (provided by PLS-Graph) of that factor's standardized and normalized indicators. We correlated factor scores with individual items to calculate cross-loadings. Boldface item loadings should be greater than cross-loadings. See the [Appendix](#) for actual item wording in surveys.

the requirement that Chin (1998) prescribed, indicating that the measures were adequate in their individual reliabilities.²

Second, to determine whether the items loaded on other constructs, as well as on their theorized construct, we computed cross-loadings (see Table 1). For cross-validated items to be included in the finalized data set, the loading must be larger on the intended construct than on any other constructs. Consequently, on determining that none of the items loaded higher on any construct other than the intended construct, we included all the items.

Using the loadings from the constructs in the model, we created composite reliabilities for the variables in the core model. The [Appendix](#) shows the items in each scale and the composite reliabilities for each construct. The results indicate that all the variables met the recommended value of 0.80 and thus are reliable.

Table 2 shows that the alpha coefficients for the items within each construct are sufficiently high (>0.70; Nunnally & Bernstein, 1994). The more accurate composite reliabilities, which avoid the assumption of equal weighting of items, were even higher; all were above the 0.90 level.

Table 2 also presents the average variance extracted and the correlations between the constructs. A comparison of the square root of the average variance extracted with the correlations among constructs indicates that, on average, each construct is more highly related to its own measures than to other constructs (Chin, 1998, p. 327).³ Moreover, all average variances extracted were well above the 0.50 recommended level (Chin, 1998). In summary, these results support the convergent and discriminant validity of our constructs.

Structural model results

Figure 2 presents the results of the data analysis using PLS-Graph. The results, which can be interpreted similarly to standardized regression betas, indicate that types of usage predict performance differentially and that routinization and infusion have different drivers. Figure 2 provides the R-squares and path coefficients, along with their respective significance levels.

Figure 2 also provides information as to which of our hypotheses were supported in this study. The relationship

² As a guideline, Chin (1998, p. 325) stated, "Standardized loadings should be greater than 0.707....But it should also be noted that this rule of thumb should not be as rigid at early stages of scale development. Loadings of 0.5 or 0.6 may still be acceptable if there are additional indicators in the block for comparison basis."

³ This is also consistent with Fornell and Larcker's (1981) recommendation that the average variance extracted should be larger than the square of the correlations (i.e., equivalent to a monotonic power transformation of numbers in the table).

Table 2 Interconstruct correlations (consistency and reliability tests for multi-item constructs)

	Cronbach's alpha	Composite reliability	Average variance extracted	ATT	PEU	UF	R	I	AP	SP
ATT – T1 attitude (3)	0.900	0.954	0.875	0.935						
PEU – projected extent of use (2)	0.824	0.919	0.699	0.651	0.836					
UF – frequency of use (3)	0.908	0.959	0.921	0.522	0.524	0.96				
R – routinization (4)	0.982	0.987	0.963	0.472	0.467	0.794	0.981			
I – infusion (3)	0.899	0.928	0.767	0.382	0.356	0.594	0.747	0.876		
AP – IT-enabled administrative performance (3)		0.905	0.762	0.356	0.348	0.457	0.606	0.589	0.873	
SP – IT-enabled salesperson performance (4)		0.902	0.699	0.205	0.244	0.309	0.442	0.583	0.527	0.836

Note: 1. Diagonals are the square root of the average extracted.

2. Cronbach's alphas are not reported for Administrative Performance and Sales Performance because they are formative indicators. Diamantopoulos and Winklhofer (2001) state that conventional procedures used to assess the validity and reliability of scales of reflective indicators (e.g., factor analysis and assessment of internal consistency) are not appropriate for composite variables (i.e., indexes) with formative indicators.

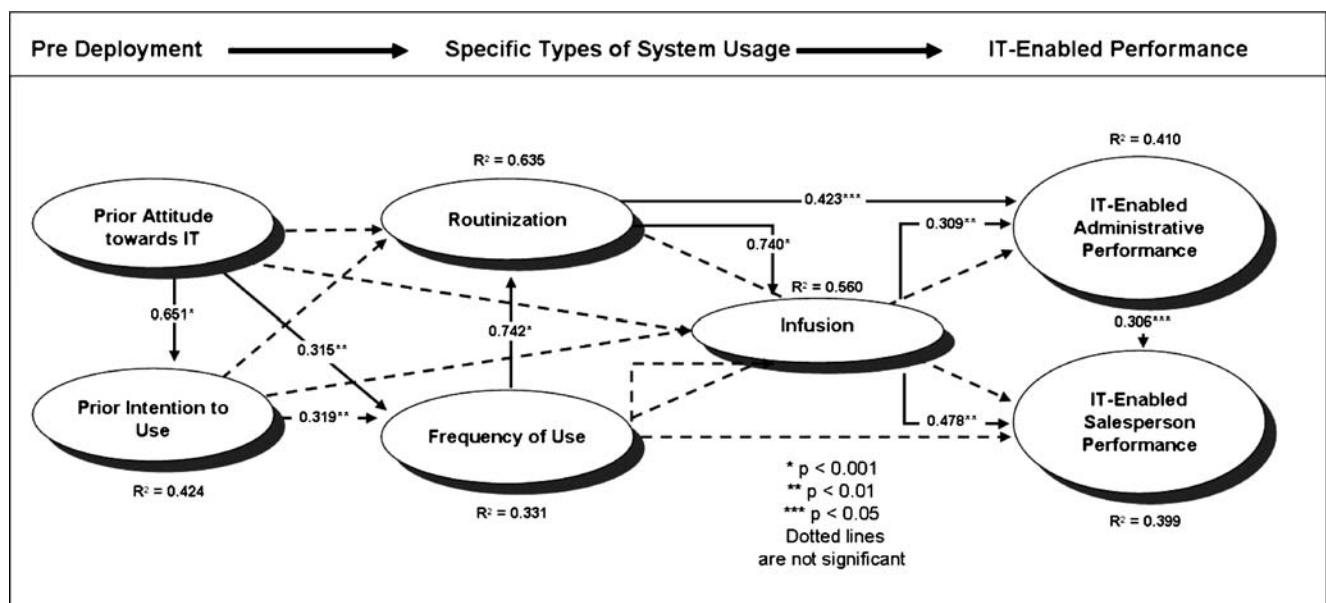
between pre-deployment attitudes and prior intentions to use the technology has previously been established (Jones et al., 2002), and we confirmed it in this study; that is, prior intention predicted the frequency of use ($b=0.319$), and attitude led to an intention to use before deployment ($b=0.651$).

Although not all the hypothesized relationships were supported, several interesting findings resulted from this study. Routinization predicts IT-enabled administrative performance ($b=0.423$) but not IT-enabled salesperson performance. Conversely, infusion affects both IT-enabled salesperson performance ($b=0.478$) and IT-enabled administrative performance ($b=0.309$).

Extent of use, the traditional measure of technology usage, seems to affect neither the salesperson's infusion of

the technology nor his or her performance. However, the frequency of current usage predicts the routinization of the technology ($b=0.742$). Furthermore, another often-used surrogate measure of technology usage, the projected intention to use the SFA technology, predicts only the actual usage frequency ($b=0.319$); it has no effect on the salesperson's routinization or infusion of the SFA technology. These results suggest that stronger intentions to use the technology before deployment and the salesperson's positive attitude go only so far to ensure that the salesperson will use the technology more frequently; it does not determine how efficiently or effectively he or she will use the technology.

To test the mediating role of the manner of use, following the three-step procedure that Baron and Kenny

**Figure 2** Statistical results.

(1986) outlined, we analyzed structural models for the mediation role of (1) infusion on frequency to sales performance, (2) routinization on frequency to sales performance, (3) infusion on frequency to administrative performance, and (4) routinization on frequency to administrative performance. In each of these cases, routinization or infusion mediated the relationship between frequency of use and the performance outcome.⁴

Discussion

The overarching goal of this exploratory research was to understand how various forms of technology usage affect multiple measures of salesperson performance. To this end, we tested a new model that links attitudes toward technology before its implementation to different types of technology usage after implementation, and we examined these effects on IT-enabled administrative performance and IT-enabled salesperson performance. Furthermore, we examined and reported types of usage as key mediating influences on salesperson performance.

For management, our results suggest that encouraging the use of technology more frequently is likely to result in the salesperson incorporating the technology into his or her daily work routine. However, he or she might not use the technology to its greatest potential. Therefore, management should deploy resources that demonstrate how the salesperson can use the technology more efficiently and effectively. This finding supports the need for more effective IT training. Our results also suggest that routinization affects infusion and IT-enabled administrative performance but not IT-enabled salesperson performance. Conversely, infusion influences both performance measures. This finding highlights the importance of infusion, as Jones et al. (2002) suggested. Infusion can enhance overall sales performance. Thus, the goal should be to get salespeople to use the technology more efficiently.

Given the impact on eventual technology usage, companies should manage salespeople's expectations of the technology before introducing it to them. Perhaps managers can engage in more focused pre-implementation campaigns that are designed to "sell" salespeople on the technology.

Our results further indicate that managing the acceptance process for SFA/CRM systems requires different strategies for each period of deployment. Before deploying the technology, management should concentrate on factors that influence initial use (for more on this topic, see Jones et al., 2002). However, although these facilitating conditions

encourage initial use, they do not necessarily lead to an increase in sales productivity. The effective and efficient use of technology is critical in ensuring that technology leads to an increase in sales productivity.

Limitations and future research

The first limitation of this research pertains to the sample, which consisted of salespeople in one company. Although restricting our study to one company enabled us to control for extraneous factors (e.g., different SFA systems, different incentive plans), it is possible that our study's results are not generalizable across the selling profession. Future research should examine the model across different industries and with different populations.

The second limitation is that our model is a series of main-effect relationships. Possible contingency variables are bonus incentives for technology use, network externalities, and the "big brother" effect. Future research should investigate contingent relationships and examine the role of facilitating conditions within the organization on routinization, infusion, and the performance outcomes.

Last, in our study, we assumed that all else was held constant, especially individual difference factors related to experience, expertise, and technology acumen. Future research could examine specific salesperson characteristics (e.g., expertise) and technology use. Given that our study demonstrates the importance of attitude toward technology before SFA deployment, future research could capture attitudes toward each of the potential uses of the technology rather than focus on the perceptions of whether technology usage overall is a "good" idea.

Note that this study has a pro-innovation emphasis in that we assumed that all technology has a positive impact on performance. Although we empirically linked this emphasis in the study, we recognize that this may not always be the case. Future research should also investigate the impact of IT-enabled administrative performance on overall sales performance.

Despite the aforementioned limitations, our research adds to the limited extant knowledge of technology use and performance and highlights the limitation of focusing solely on the extent of usage as an indicator of the success of the SFA/CRM system. We hope this research inspires others to examine the important issue of helping organizations and customer-contact employees obtain a satisfactory return on investment on technology geared toward gathering and disseminating market intelligence. Future research in this area would generate a deeper understanding of sales force productivity and enhance future strategic deployments of SFA/CRM systems in the sales organizations of tomorrow.

⁴ We also tested the mediating role of intention and frequency of use on prior attitudes and found that it was consistent with the traditional attitude-behavior literature.

Appendix

Projected extent of use

Table 3 Definition: the a priori frequency with which the salesperson projects that he or she will use the technology (Azjen, 1985; Davis, 1989; Taylor & Todd, 1995)

	Factor loadings	Less than once a month	Once a month	A few times a month	A few times a week	About once a day	Several times a day	
1. On average, how frequently do you expect to be using [technology] for your work when it becomes available?	0.915	1	2	3	4	5	6	
2. Once it becomes available, how frequently do you see yourself using [technology] for your job?	0.930	Extremely infrequent –3	Very infrequent –2	Somewhat infrequent –1	Neither 0	Somewhat frequent 1	Very frequent 2	Extremely frequent 3

Pre-deployment attitude

Table 4 Definition: the a priori overall attitude toward the usage of the new system (Davis, 1989; Davis et al., 1989)

Overall, using [the technology] is a ____ idea									
Factor loading									
1. 0.976	Bad	–3	–2	–1	0	1	2	3	Good
2. 0.956	Foolish	–3	–2	–1	0	1	2	3	Wise
I ____ the idea of using FV									
Factor loading									
3. 0.871	Dislike	–3	–2	–1	0	1	2	3	Like

Frequency of use

Table 5 Definition: the frequency with which the salesperson uses the technology (Taylor & Todd, 1995)

	Factor loadings	Less than once a month	Once a month	A few times a month	A few times a week	About once a day	Several times a day	
1. On average, how frequently have you been using [technology] for your work?	0.956	1	2	3	4	5	6	
4. Since it became available, how frequently have you been using [technology] for your job?	0.964	Extremely infrequent –3	Very infrequent –2	Somewhat infrequent –1	Neither 0	Somewhat frequent 1	Very frequent 2	Extremely frequent 3

Routinization

Table 6 Definition: the extent to which the use of the technology has been integrated into the salesperson's normal work routine (Saga & Zmud, 1994)

Statement	Factor loadings	Strongly disagree	Neither				Strongly agree		
1. My use of [technology] has been incorporated into my regular work schedule.	0.976	−3	−2	−1	0	1	2	3	
2. My use of [technology] is pretty much integrated as part of my normal work routine.	0.989	−3	−2	−1	0	1	2	3	
3. My use of [technology] is a normal part of my work.	0.980	−3	−2	−1	0	1	2	3	

Infusion

Table 7 Definition: the extent to which a salesperson fully uses the technology to enhance his or her productivity (Jones et al., 2002)

Statement	Factor loadings	Strongly disagree	Neither				Strongly agree		
1. I am using [technology] to its fullest potential for supporting my own work.	0.955	−3	−2	−1	0	1	2	3	
2. I am using all capabilities of [technology] in the best fashion to help me on the job.	0.957	−3	−2	−1	0	1	2	3	
3. I doubt that there are any better ways for me to use [technology] to support my work.	0.663	−3	−2	−1	0	1	2	3	
4. My use of [technology] on the job has been integrated and incorporated at the highest level.	0.893	−3	−2	−1	0	1	2	3	

IT-enabled administrative performance—indicators modeled as formative variables

Table 8 Definition: the extent to which the technology affects the quality of the salesperson's call planning and time and expense management (created for this study)

To what extent has [technology] affected the quality of your performance with regard to:

Statement	Factor loadings	Strongly negative			Neither			Strongly positive		
1. Management of time	0.883	−3	−2	−1	0	1	2	3		
2. Planning ability	0.926	−3	−2	−1	0	1	2	3		
3. Management of expenses	0.805	−3	−2	−1	0	1	2	3		

IT-enabled salesperson performance—indicators modeled as formative variables

Table 9 Definition: the extent to which the technology affects the quality of the salesperson's ability to produce key sales results (created for this study)

To what extent has [technology] affected the quality of your performance with regard to:									
Statement	Factor loadings	Strongly negative	Neither			Strongly positive			
1. Selling high profit-margin products	0.684	−3	−2	−1	0	1	2	3	
2. Generating a high level of dollar sales	0.871	−3	−2	−1	0	1	2	3	
3. Quickly generating sales of new company products	0.892	−3	−2	−1	0	1	2	3	
4. Exceeding sales targets	0.879	−3	−2	−1	0	1	2	3	

References

- Ahearne, M., Jelinek, R., & Rapp, A. (2005). Moving beyond the direct effect of SFA adoption on salesperson performance: Training and support as key moderating factors. *Industrial Marketing Management*, 34(4), 379–388.
- Ahearne, M., Srinivasan, N., & Weinstein, L. (2004). Effect of technology on sales performance: Progressing from technology acceptance to technology usage and consequence. *Journal of Personal Selling & Sales Management*, 24, 297–310 (Fall).
- Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(4), 411–423.
- Avlonitis, G. J., & Panagopoulou, N. G. (2005). Antecedents and consequences of CRM technology acceptance in the sales force. *Industrial Marketing Management*, 34(4), 355–368.
- Azjen, I. (1985). From intention to actions: A theory of planned behavior. In J. Kuhl & J. Beckmann (Eds.), *Action control: From cognition to behavior*. Berlin Heidelberg New York: Springer.
- Barker, T. A. (1999). Benchmarks of successful sales force performance. *Canadian Journal of Administrative Sciences*, 16, 95–104 (June).
- Baron, R., & Kenny, D. A. (1986). The moderator–mediator distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182.
- Behrman, D. N., & Perreault, W. D., Jr. (1984). A role stress model of the performance and satisfaction of industrial salespersons. *Journal of Marketing*, 4(48), 9–21.
- Benbasat, I., & Zmud, R. W. (2003). The identity crisis within the IS discipline: Defining and communicating the discipline's core properties. *MIS Quarterly*, 27(2), 183–194.
- Chin, W. W. (1998). The partial least squares approach for structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Mahwah, NJ: Erlbaum.
- Cooper, R. B., & Zmud, R. W. (1990). Information technology implementation research: A technological diffusion approach. *Management Science*, 36(2), 123–139.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13, 319–339 (September).
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982–1003.
- Diamantopoulos, A., & Winklhofer, H. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, 38(2), 269–277.
- Erffmeyer, R. C., & Johnson, D. A. (2001). An exploratory study of sales force automation. *Journal of Personal Selling & Sales Management*, 21(2), 167–176.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50.
- Galvin, J., & Berg, T. (2003). CRM business transformation: More than just technology. *Gartner Group Research Report R-20-1330*. Gartner Group.
- Gerbing, D. W., & Anderson, J. C. (1985). The effects of sampling error and model characteristics on parameter estimation for maximum likelihood confirmatory factor analysis. *Multivariate Behavioral Research*, 20(3), 255–271.
- Gohmann, S. F., Barker, R. M., Faulds, D. J., & Guan, J. (2005). Sales force automation, perceived information accuracy and user satisfaction. *Journal of Business and Industrial Marketing*, 20(1), 23–32.
- Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 19(2), 213–236.
- Honeycutt, E. D., Jr., Thelen, T., Thelen, S. T., & Hodge, S. K. (2005). Impediments to sales force automation. *Industrial Marketing Management*, 34(4), 345–354.
- Jones, E., Sundaram, S., & Chin, W. (2002). Factors leading to sales force automation use: A longitudinal analysis. *Journal of Personal Selling & Sales Management*, 22(3), 145–156.
- Ko, D.-G., & Dennis, A. R. (2004). Sales force automation and sales performance: Do experience and expertise matter? *Journal of Personal Selling & Sales Management*, 24, 311–322 (Fall).

- Kwon, T. H., & Zmud, R. W. (1987). Unifying the fragmented models of information systems implementation. In R. J. Boland & R. A. Hirschheim (Eds.), *Critical issues in information systems research*. Hoboken, NJ: Wiley.
- MacCallum, R. C., & Browne, M. W. (1993). The use of causal indicators in covariance structure models: Some practical issues. *Psychological Bulletin*, 114(3), 533–541.
- MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, 1(2), 130–149.
- Morgan, A. J., & Inks, S. A. (2001). Technology and the sales force. *Industrial Marketing Management*, 5, 463–473 (July).
- Morris, M. H., Davis, D. L., Allen, J. W., Avila, R. A., & Chapman, J. (1991). Assessing the relationship among performance measures, managerial practices, and satisfaction when evaluating the sales force: A replication and extension. *Journal of Personal Selling & Sales Management*, 11(3), 25–35.
- Nunnally J., & Bernstein, J. C. (1994). *Psychometric theory* (3rd ed.). New York: McGraw-Hill.
- Oliver, R. L., & Anderson, E. (1994). An empirical test of consequences of behavior and outcome-based sales control systems. *Journal of Marketing*, 58, 53–67 (October).
- Rangarajan, D., Jones, E., & Chin, W. (2005). Impact of sales force automation on technology-related stress, effort, and technology usage among salespeople. *Industrial Marketing Management*, 34 (4), 345–354.
- Rivers, M. L. & Dart, J. (1999). The acquisition and use of sales force automation by mid-sized manufacturers. *Journal of Personal Selling & Sales Management*, 19(2), 59–73.
- Saga, V. L., & Zmud, R. W. (1994). The nature and determinants of IT acceptance, routinization and infusion. In L. Levine (Ed.), *Diffusion, transfer and implementation of information technology* (pp. 67–86). Amsterdam: Elsevier.
- Shimp, T., & Kavas, A. (1984). The theory of reasoned action applied to coupon usage. *Journal of Consumer Research*, 11, 795–809 (December).
- Speier, C., & Venkatesh, V. (2002). The hidden minefields in the automation of sales force automation technologies. *Journal of Marketing*, 66, 98–111.
- Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research*, 6(2), 144–176.
- Thetgyi, O. (2000). Radical makeovers. *Sales and Marketing Management*, 152(4), 78–85.
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
- Zmud, R. W., & Apple, E. L. (1992). Measuring technology incorporation infusion. *Journal of Product Innovation Management*, 9(2), 148–155.