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On conceptualizing, measuring, and managing augmented technology use in business-to-business sales contexts

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ABSTRACT

Business-to-business (B2B) salespeople use a portfolio of technology tools to augment their performance of tasks. Using data from two sales forces for large multi-national consumer goods firms, this study demonstrates that applying different measures of technology use yields different estimates on returns, even for bivariate correlations among measures and constructs. Thus, given differences at a bivariate level, for the typically more complex multivariate model specifications of sales technology use, resulting parameter estimates can be misleading. Researchers can lower the resulting bias by appropriate alignments among theory (conceptualization) and measurements. This research argues that a holistic measure of sales tech-nology (ST) use (a whole) does not equate to the sum of different types of uses (intermediate measures such as using technology to access, analyze, and communicate information) or the sum of different technology tools (the individual parts). Findings indicate that outcomes differ depending on how technology use is conceptualized and measured.

1. Introduction

Much attention in practice and scholarship has been directed toward understanding the impacts of sales technology on sales force operations. Investments in sales technology (ST) tools represent significant costs for business-to-business (B2B) sales operations. Total economic demand for customer relationship management (CRM) software alone supports an expanding $24B annual revenue industry (Statista 2017)—and an ever-expanding array of information technologies. Beyond the contemporary concerns with leveraging social media, a B2B sales organization's ST portfolio may include several malleable tools (e.g., e-mail, spreadsheets, graphics software, and cell phones) as well as purpose-specific tools (e.g., order entry, order status, and contact management software). As successful implementation of ST tools is challenging, the costs for ST systems—even for successful implementations—go well beyond providing salespeople with a cell phone, social media accounts, and a laptop with CRM software installed. Yet, embracing ST is an imperative in practice as several empirical studies across multiple sales contexts demonstrate that sales technology has important direct or indirect impacts on key aspects of sales performance (Agnihotri, Gabler, Itani, Jaramillo, & Krush, 2017; Agnihotri, Kothandaraman, Kashyap, & Singh, 2012; Ahearne, Jones, Rapp, & Mathieu, 2008; Hunter & Panagopoulos, 2015; Hunter & Perreault, 2006, 2007; Lacoste, 2016; Ogilvie, Agnihotri, Rapp, & Trainor, 2018; Onyemah, Swain, & Hanna, 2010; Rapp, Beitelspacher, Schillewaert, & Baker, 2012; Wang, Dou, & Zhou, 2012).

1.1. Origins of contemporary sales technology research

Given its prominent imperative for use in practice, it is perhaps not surprising that ST research has emerged as one of four major intellectual cornerstones of modern sales research (Schrock, Zhao, Hughes, & Richards, 2016). Schrock et al. (2016) use bibliometrics methods to identify the two most influential papers in the ST use domain—a study by Speier and Venkatesh (2002) on factors associated with rejection (adoption) of SFA technology and a study by Hunter and Perreault (2007) on the antecedents and consequences of different types of ST use on relationship building (indirectly through relationship-forging tasks) and internal administrative performance. While Speier and Venkatesh (2002) focus more narrowly on the pitfalls of sales force automation (SFA) software, this paper adopts the perspective that SFA tools, like CRM tools, can be viewed as components of ST tools (Hunter, 2011). This paper adopts that broader definition of sales technology as "information technologies that facilitate or enable the performance of sales tasks" (Hunter & Perreault, 2007, p. 17). As such, ST tools run the gamut of information technology tools used by

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salespeople—including past, present, and future innovations in IT used by salespeople.

1.2. Clarifying key terms in ST research: automation versus augmentation

This paper builds on the latter of those two papers by centering on sales technology use—its conceptualization, measurement, and management. It's important to note that clarity in definition is vital to conceptualization of ST use. Such clarity requires thinking beyond some of the extant jargon and acknowledging that sales managers and scholars often use the terms SFA, CRM, and ST interchangeably. However, with the increased precision in conceptualization and measurement advocated herein, sales scholarship can play a vital role in providing clarity and guidance to managers in information technology and sales on how best to assess the resulting returns from their significant investments in IT portfolios. This call for clarity centers on aiding the advance of ST research, and is based on a premise that a valid construct requires, and even begins with, a clear conceptualization (Clark & Watson, 1995). For example, clarity in what one means by "automation" is needed in sales settings. Here, "automation" refers to "the execution by a machine agent (usually a computer) of a function that was previously carried out by a human" (Parasuraman & Riley, 1997, p. 231). With that definition, estimates indicate that as much as 40% of sales work will be automated over the next 15 years through artificial intelligence and machine learning, yet the "human touch" aspect of professional selling will still be needed for tasks not prone to automation (Baumgartner, Hatami, & Valdivieso, 2016). Most importantly, automation differs from augmentation—and many scholars call for a better understanding of how augmentation provides a means for getting beyond automation (Davenport & Kirby, 2015). A strategy for automating a sales force stands in stark contrast to an augmentation strategy. As summarized by Davenport and Kirby (2015, p. 60),

"Automation starts with a baseline of what people do in a given job and subtracts from that. It deploys computers to chip away at the tasks humans perform as soon as those tasks can be codified. Aiming for increased automation promises cost savings but limits us to thinking within the parameters of work that is being accomplished today. Augmentation, in contrast, means starting with what humans do today and figuring out how that work could be deepened rather than diminished by a greater use of machines."

Sales scholars have begun to highlight this distinction. Of note, in a forward-looking conceptual paper, Jelinek (2013, p. 639) states, "technology is meant to *augment* [emphasis added] the salesperson's abilities, improve organization, and sharpen communication and presentation, but the system itself will not destroy old, bad sales habits." Of note, this contemporary view of ST use of tools to *augment* aligns with the extant definition of ST use; that is, augmenting—which generally refers to making a process better by adding something (e.g., a technology tool) to it—is defined here as simply "facilitating or enabling the performance of a sales task." As such, given these semantics and clarifications, while not using the term "augmentation," several well-cited and recent ST papers adopt the Hunter and Perreault (2007) definition for sales technology—and view the tools as supplements to the salesperson's work. In fact, among other studies, some highly influential ST research indicates a fairly widespread embrace of the notion that ST use refers to augmenting (facilitating or enabling) sales tasks (Agnihotri et al., 2012; Agnihotri, Trainor, Itani, & Rodriguez, 2017; Ahearne et al., 2008; Hunter & Panagopoulos, 2015; Hunter & Perreault, 2006, 2007; Lacoste, 2016; Ogilvie et al., 2018; Onyemah et al., 2010; Rapp et al., 2012; Wang et al., 2012). Thus, while augmentation terminology is more recent, the extant ST research, upon which this study is based, plays a leading role in advancing the study of augmentation (in B2B sales and other settings).

Importantly, given ST's established impact on sales performance, customer satisfaction, turnover, commitment, and such—coupled with the pending imperative for sales managers to consider new innovations that fully *automate* sales tasks—it is vital to modern sales research to conceptualize, measure and include the impacts of ST use. This paper contributes to the advance of ST research by demonstrating the importance of clarity in conceptualization and measurement of ST use—and demonstrates empirically that different measures of ST use have different effects on key sales behaviors and aspects of sales performance.

1.3. Contributions and preview of this research

This research contributes to the extant literature by showing that a researcher's conceptualization and choice of an ST use measure matters—theoretically (with interpreting parameter estimates) and managerially (when assessing returns from ST use). As shown herein, different measures of ST use yield different parameter estimates for the returns provided by ST use—and thus yield different conclusions and implications for both advancing ST scholarship (e.g., confirming or denying hypotheses) and sales practice (e.g., assessing returns on investments in ST tools). It also contributes by seeking new ways to improve the clarity in ST measurement and hypotheses testing while demonstrating that—even at a bivariate level—results or assessment of returns from ST investments differ based on the manner through which ST use is measured. Finally, this study contributes to sales practice by demonstrating a means through which a firm can audit and assess returns on their oft-substantial investments in sales technology, including returns on behavioral tasks, purpose-specific ST tools, and key aspects of performance.

This paper is the first to investigate interrelationships among the major types of ST use measures—and empirically tests the relationships among these alternative measures of use as well as their interrelationships with sales behaviors (e.g., smart selling and relationship-forging tasks) and key aspects of performance (internal and external salesperson responsibilities). The research seeks to contribute insights on how sales managers and scholars can better assess returns on ST investments by congruent conceptualizations (and corresponding model specifications) with appropriate levels of sales tasks, ST use, and sales outcomes. Specifically, the study shows that measures of technology use that are holistic (aggregated or direct), intermediate purpose-specific (e.g., using ST for accessing, analyzing, or communicating information), and disaggregated (malleable tools like e-mail or purpose-specific tools like cell phones) produce different effects on work behaviors and outcome measures. In doing so, the study advocates for the critical attention of managers and scholars in detailing specificity in their measurement of ST use.

The next section includes a brief review of relevant literature for developing hypotheses of interrelationships among ST use, sales behaviors, and key aspects of performance. While this paper uses the context of professional selling—which may be the domain of use accounting for the largest and fastest growing industrial costs for technology tools (e.g., SFA and CRM industries)—many of its questions are germane to broader work contexts associated with IT use.

2. Aligning measurement with conceptualizations of ST use

2.1. Relevant technology use and sales technology literature

Research outside the sales domain has analyzed broader sectors through which scholars have studied the impact of IT on overall industries. For instance, based on an industry-level analysis, Hu and Quan (2005) show the effects of IT investments across industries and propose proper level moderators of those effects. Early research on the "IT Productivity Paradox" (Roach, 1987) generated a better understanding of why technology investments do not always lead to productivity gains. Meanwhile, innovations in technology, such as advances in artificial intelligence, create demonstrable increases in productivity and potential gains for society. At industry levels of analyses, however, measures of productivity continue to decline—creating a new productivity paradox that warrants attention associated with the current second machine age (Brynjolfsson & McAfee, 2014). Such industry- or firm-level studies often employ industry- or firm-level units of analysis to compare sales to investments in technology, with the ratio representing productivity. Such studies represent a "black box" approach to technology's impact and have proven useful for a high-level understanding of assessing returns from technology investments. Yet, providing insights to sales managers and scholars is typically outside the scope of such studies.

Within the firm, technology plays a key role in both strategic planning and functional level accountability. For example, Kumar (2015) argues that insights gained through IT applications of sophisticated quantitative methods provide the corporate boardroom with better means for accountability—particularly for marketing and sales activities. That accountability can be complex, as ST uses involve interactions among technology, people, and processes. Nonetheless, economic realities and the nature of competition provide strong incentives for managers and scholars to not only embrace new technologies, but to understand how they impact performance and productivity. It's worth noting that current research indicates the higher the level of investigation, the cruder the measure of use. While contributing relevant assessments of technology returns, such "black box" studies are designed at a broad level and thus fail to capture the detailed micro-level behaviors that are of focal interest to practicing sales managers.

2.2. The vital role of measurement in research on ST use

Indeed, conceptualization and measurement are of concern to advancing a shared understanding in this research domain. Simply relying on existing secondary data collections—while convenient for research purposes—falls well short of providing a panacea for concerns about research bias, or other demand artifacts, associated with primary measurement. Specifically, secondary data relies on measures developed for other purposes that often lack the specificity in definition and operationalization needed for statistical validity—and rarely include theoretically-supported and demonstrably-relevant predictors disclosed by a thriving ST literature. More precision in *how ST use is conceptualized and measured* is required to advance science in the ST domain. With inconsistency across studies—particularly on the levels at which technology use occurs (e.g., tool-level, purpose-specific, or holistic use)—insights are limited.

In the information systems literature—and moving toward intermediate levels of use with a technology-centric conceptualization—Zablah et al. (2012) propose using measures based on grouping the use of different tools based upon the tools' intended functionality: CRM prioritization tool use (i.e., tools used prior to the sales interaction with customers, involving marketing, sales, and service resource allocations) and CRM interaction support tool use (i.e., tools used to support activities that enhance customer information gathering, customer information sharing, and inter-functional employee coordination). In this conceptualization, intermediate measures are simply the indexed sum of use across individual tools. This conceptualization represents a hybrid "black box" approach by maintaining its focus on firm-level outcomes, while integrating some primary data collection on individual tool use. However, by aggregating tool uses into summary indices, the approach does not allow assessment of returns at the individual technology use level. Yet, such an approach may fit well with a sales organization's interests in assessing a class (or subset) of tools from their ST portfolio.

While outcomes at the firm level fit with measuring technology use through those firms' investments in technology, using such "black box" measures may hide other meaningful managerial and scholarly insights. For example, managers often seek insights at the individual technology procurement level (e.g., the effect of cell phone or database analysis software use on work behaviors and outcomes). Plus, they often seek insights on whether they realize returns from that specific technology. In scholarship, theories such as task-technology fit (Goodhue & Thompson, 1995) are helpful. However, technology tools are malleable for use across different sets of tasks—and users (salespeople) have different skill levels with using such tools. Thus, a more micro-level analysis may be appropriate.

2.3. Model specification considerations when measuring ST use

A burgeoning ST literature explores how technology use has had unprecedented effects on modern go-to-market sales processes in B2B markets. The need to improve efficiency and effectiveness (Hunter & Perreault, 2007; Rapp, Agnihotri, & Forbes, 2008) motivates ST research ranging from employing the latest CRM tools (Agnihotri, Trainor, et al., 2017; Rapp, Trainor, & Agnihotri, 2010; Tanner, Ahearne, Leigh, Mason, & Moncrief, 2005) to temporal intermediate CRM purposes (Zablah, Bellenger, Straub, & Johnston, 2012) to leveraging social media (Agnihotri et al., 2012; Agnihotri, Dingus, Hu, & Krush, 2016). Also, ST research contexts include, among others, B2B services (Rangarajan, Chonko, Jones, & Roberts, 2004), business to consumer packaged goods resellers (Hunter & Perreault, 2006, 2007), pharmaceutical sales (Ahearne et al., 2008; Hunter & Panagopoulos, 2015), direct selling environments (Harrison & Hair, 2017; Sharma & Sheth, 2010), and studies sampling across a range of salespeople in B2C and B2B industries (Schillewaert, Ahearne, Frambach, & Moenaert, 2005). Moreover, the endogenous outcome variables predicted from behavioral sales process models range from early outcomes of ST use focused on key aspects of performance, such as building relationships with customers (effectiveness) and improving administrative efficiency (Hunter & Perreault, 2007). Other recent research heightens our understanding of how ST use influences job satisfaction (Limbu, Jayachandran, & Babin, 2014). Given the range of contexts and outcomes predicted, it's not surprising that subsequent application of a range of different ways for measuring technology use further confounds results and leads to a continuous cycle of ambiguous results from ST investments.

2.4. Conceptualizing ST use: holistic, intermediate, and disaggregate measures of use

Categorical conceptualizations of ST use include holistic, intermediate, or disaggregated measures. At the extremes, holistic measures reflect general use of the portfolio of IT tools, while disaggregated measures reflect the use of an individual technology tool, or the functionality with a package (e.g., contact management as part of a CRM or SFA suite). Whereas much ST use measurement and optimization began by considering individual technology tools, the trend toward holistic and intermediate ensued. Among others contributing to early studies on sales technology, Collins (1985) focused on how salespeople could optimize spreadsheet use. Meanwhile in the information systems literature, scholars converged on reliance on self-reported measures of use of the extent of use (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Davis, 2000) versus undisclosed measures of actual system use (Collopy, 1996), a research shift that was potentially aided by rising concerns of users about privacy and workarounds by users to distort such measures by fainting use. Likewise in the ST literature, several studies (Hunter & Panagopoulos, 2015) adapted items from the measure of ST infusion proposed by Jones, Sundaram, and Chin (2002). ST infusion is a direct self-reported measure of holistic ST use that gets beyond only measuring extent of use to emphasize that one's quality of use may vary (Sundaram, Schwarz, Jones, & Chin, 2007). To gain a richer understanding of how technology was being used by salespeople, Hunter and Perreault (2007) proposed three intermediate measures of ST use for accessing, analyzing, and communicating information. Another type of measure, proposed herein, uses such intermediate measures to form a composite representing a holistic measure of ST use (e.g., a second-order factor), referred to here as "holistic ST use" (aggregated).

To conceptualize how ST use fits a given study, it may be helpful to begin at either a holistic or at the disaggregated (or functional) level (e.g., an individual tool like a spreadsheet or a social media platform). However, managers often procure ST tools to improve the sales organization's capacity to accomplish specific purposes. At the broadest conceptual level of use, Hunter (2011, p. 429) provides a Venn diagram of ST illustrating how both sales-based CRM and SFA applications are sales technology's two major overlapping components—both of which represent costly investments to modern sales firms. On the other hand, at the most disaggregated level (e.g., at the functionality or individual tool level), practicing sales and IT managers often conduct assessments to determine which ST tools are producing intended results.

However, without insights on the mechanisms through which such results are achieved, spurious relationships often emerge. To help link use of tools to outcomes, intermediate purpose-specific measures of use (e.g., accessing, analyzing, and communicating) often bridge the gap between sales performance outcomes and the use of an individual tool. Such intermediate purpose-specific measures of use add specificity which can help scholars develop more conceptually rigorous hypothetical models. From a practicing sales manager's perspective, since sales organizations rely on a variety of ST tools, a more comprehensive and detailed audit of a firm's ST portfolio should include measures of ST use at all three levels. The different levels of use measures can then be related to relevant sales behaviors and performance outcomes, as demonstrated herein.

3. Behavioral mechanisms influencing the effects of ST use on performance outcomes

3.1. Working smarter (with technology) versus harder (without it)

Technology use often has indirect effects on key sales performance outcomes, and the mechanisms for understanding how use impacts performance has been a dominant focus in both the IT use and ST use literatures. In the IT productivity literature, researchers often assume the tool works if only the user adopts it—which generates an extensive literature on motivating adoption. Mithas, Tafti, Bardhan, and Mein Goh (2012) summarize four major arguments for null findings associated with IT productivity: (1) competitive effects, (2) the changing nature of IT systems, (3) data or modeling issues, and (4) the level of analysis. This paper focuses mainly on the latter of these four concerns.

Three studies on the level of analysis are useful foundations for comparison with this work. As Aral and Weill (2007) "unpacked" the firm-level measures of IT investments, this study shows how unpacking such IT use also matters at the user level. Additionally, Banker, Bardhan, Chang, and Lin (2006) focused on a manufacturing context, while this study centers on contexts more malleable for both tools and tasks. Using the Resource-based View (RBV) perspective employed in Banker et al.'s study, the manufacturing context provides managers with better control over users in managing task and technology use. Finally, Mithas, Krishnan, and Fornell (2005) focus on the purpose-specific software application—namely, CRM software—to study how investments in CRM applications have firm-level effects. Observation measures are inappropriate as users function mainly out of sight of management and are free to tailor tasks and technology use in idiosyncratic ways that fit their objectives.

Sujan (1986) proposed that, while most of the research on sales centered on motivating harder work (e.g., do more sales calls), Weiner's (1980) theory on motivation provides a basis for considering factors that motivate "working smarter." Importantly, Sujan's (1986) research predated the surge in technology investments by sales organizations that yielded two modern-day IT industries—SFA and CRM. Ironically, the shift from SFA to CRM may have paralleled management concern with using technology to improve efficiency (e.g., SFA) toward improving effectiveness (e.g., CRM). More recent research in a B2B sales context notes that IT use facilitates or enables the performance of key tasks. Smarter working tasks are eventually critical to realizing returns from technology use on effectiveness. Namely, these new "smarter working" tasks—relationship-forging tasks—mediate the effects of technology use on building effective relationships with business customers (Hunter & Perreault, 2007).

3.2. How working smarter (with technology) helps forge stronger business relationships

Seminal research on working smart also integrates contributions on adaptive selling (Spiro & Weitz, 1990; Sujan, 1986; Sujan, Weitz, & Kumar, 1994), which highlight the importance for salespeople to tailor behaviors to best meet the needs of specific customers. The ensuing "smart-selling literature" found that more effective salespeople tailor their behaviors to fit key sales tasks (Hunter, Bunn, & Perreault, 2006; Hunter & Perreault, 2007; Spiro & Weitz, 1990; Sujan et al., 1994; Sujan, Sujan, & Bettman, 1988) and plan for their interactions with buyers (Gwin, 1979; Gwin & Perreault, 1981; Hunter, 2014; Sujan et al., 1994).

The current literature recognizes two widely accepted "working smarter" tasks: tailoring behaviors to specific customers (i.e., "adaptive selling" or proposing mutually beneficial ideas) and planning for upcoming meetings (i.e., a buyer-seller face-to-face interaction). Adaptive selling—or tailoring one's behavior to the needs of the situation—is an inherently human task that may be replete with applications of tacit knowledge. A similar adaptation would be interactively developing and proposing ideas that benefit both the buyer and the seller as is done with an integrative sales negotiation approach—in contrast to simply "pushing" the seller's products on the buyer, which is associated with a distributive sales negotiation approach. Here, we define "planning" as the extent to which users (salespeople) engage in efforts to discover the suitability of their behaviors and activities. Planning, thus, should be a central construct in IT-productivity studies as it is relevant to the tenets of task-technology fit theory. Research suggests that "smart-selling" tasks are facilitated or enabled by holistic ST use, yet this study argues the effects depend on how technology use is measured.

4. The potential benefits of technology-influenced sales behaviors

4.1. Job and sales performance

Ray, Muhanna, and Barney (2005) argue that research should apply the Resource-Based View (RBV) at the process level, rather than the firm level, to better understand how investments in a critical resource (IT) help organizations realize returns on efficiency and effectiveness. Particularly when focusing at firm-level analyses, the ST literature has employed the RBV to gain better understanding of resource capabilities such as a firm's aggregate investments in the use of social media (Trainor, Andzulis, Rapp, & Agnihotri, 2014) and CRM technology (Rapp et al., 2010). As focal outcomes associated with individual-level outcomes that ultimately contribute to an RBV perspective, effectiveness and efficiency represent two intermediate outcomes, and hallmarks for social science research. In a sales context, sales relationship effectiveness is defined as the extent to which the salesperson cultivates a sales relationship that works for both the selling and buying firms (Hunter & Perreault, 2006). Administrative efficiency reflects the salesperson's ability to complete required reports promptly (Hunter & Perreault, 2006). By individually evaluating these aspects of performance, the extant research provides mechanisms through which ST use, smart selling behaviors, and combinations of both relate to performance outcomes.

Like other boundary spanners, salespeople typically have responsibility for tasks both outside and inside their organizations. This study

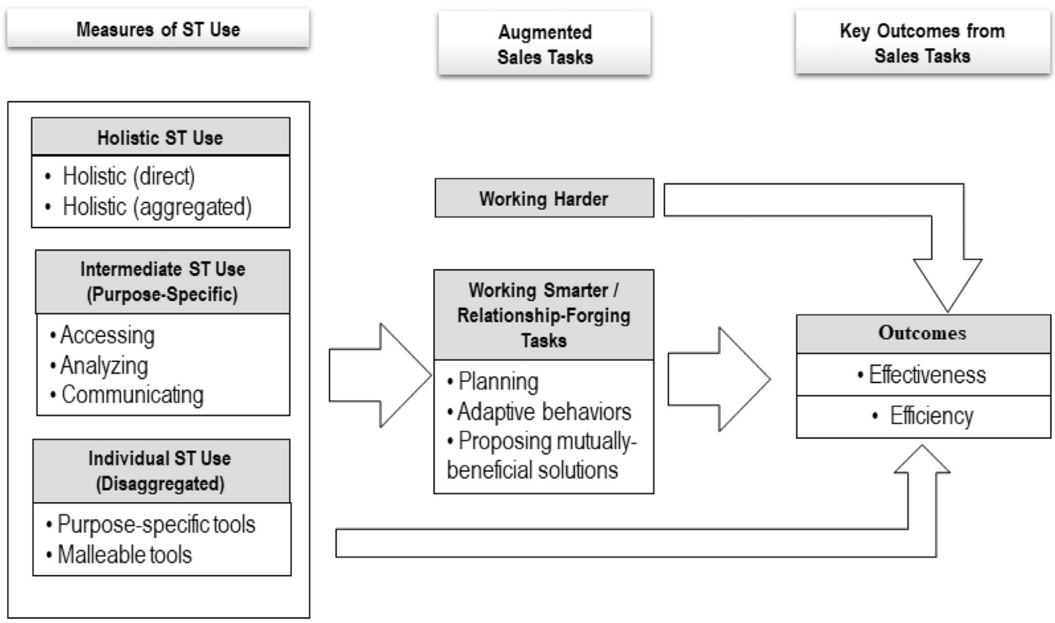

Fig. 1. Conceptual model of pervasiveness and types of technology use.

evaluates how IT use and selling smart influence two specific aspects of performance: sales relationship effectiveness (which is focused primarily on external performance) and administrative efficiency (which is focused primarily on internal performance).

4.2. Holistic technology use and key performance outcomes

Fig. 1 outlines a conceptual model of technology uses. As shown, individual technology may be used by people for either the purposes they were designed (i.e., non-malleable tools), or they may be used for malleable purposes. As noted in previous research, three of the major purposes for technology use are accessing, analyzing, and communicating information (Hunter & Perreault, 2007). Additionally, in a sales context, salespeople may use IT to improve their results in ways not captured by the two selling-smart constructs.

Behavioral process models such as the Technology Acceptance Model and its variants (Davis, 1989; Venkatesh & Davis, 2000) represent mechanisms, as they build on behavioral theories (e.g., Fishbein and Ajzen's Theory of Reasoned Action), through which people perform different tasks by using technology to improve performance outcomes. Such process-level models can provide richer insights into how and why users employ technology tools and can be helpful toward encouraging adoption. For example, Beaudry and Pinsonneault (2005) show how coping mechanisms play key roles in user adoptions and may have negative impacts on adoption behaviors—particularly when a user perceives IT use as a threat. Recent research on the individual use of malleable information technologies (Schmitz, Teng, & Webb, 2016) provides new insights while introducing new challenges for researchers by building on adaptive structuration theory (DeSanctis & Poole, 1994). These studies recognize the reality that technologies provide initial structures for users who may then adapt new task structures for innovative uses of technology tools. Those adaptations may yield differential returns from technology use.

Information technology affects an individual's effectiveness and efficiencies in ways that may go beyond (or fall short of) the technology's initially intended purposes. For example, in the sales context, SFA tools are designed primarily to improve efficiencies, whereas CRM tools focus on improving effectiveness—particularly with building customer relationships (Hunter & Perreault, 2007). Most modern salespeople focus on building effective relationships with buying firms and are likely to use technology to improve their sales relationship effectiveness. In such roles, technology can help salespeople both to access information from previous sales interactions and include that information in subsequent interactions. Sales technology can also help salespeople be more efficient in completing non-selling administrative tasks. For example, time and territory management software can improve a salesperson's ability to coordinate administrative chores and to complete required reports on time. Administrative efficiency represents another aspect of sales performance. Specifically, we expect holistic ST use will correlate positively with efficiency (internal administrative task) and effectiveness (external relationship tasks).

H1. Holistic ST use relates positively to sales relationship effectiveness.

H2. Holistic ST use relates positively to administrative efficiency.

4.3. Working smarter and key performance outcomes

Consistent with previous ST research, technology use often does not influence outcomes directly; instead, it often influences the performance of key tasks, which, in turn, yield performance outcomes (Ahearne et al., 2008; Hunter & Perreault, 2007). Key sales tasks that influence performance results include both proactive (e.g., planning) and reactive behaviors (adaptive behaviors). Several studies have found that adaptive selling has a positive influence on sales performance (Franke & Park, 2006). Additionally, Hunter (2014) found that sales planning for interactions with customers, particularly when market driven, can improve customer relationships as well as administrative efficiency. Thus, we hypothesize that sales planning will affect sales performance as follows:

H3. Planning and adaptive behaviors relate positively to effectiveness.

H4. Planning and adaptive behaviors relate positively to efficiency.

4.4. Holistic technology use and working smarter

Information technology can assist in tailoring sales reports and market analyses to specific accounts—and those accounts' likely issues or concerns. Thus, during the sales interaction, ST can improve a salesperson's capacity to adapt presentations for each specific customer, as well as reduce the effort needed to access and present relevant information in response to buyer objections. Further, technology use can improve the salesperson's practice of adaptive selling behaviors before the sales interaction. For example, in the consumer-packaged goods industry, shelf-space management software such as Scorpion Planogram allows the salesperson to create plans that meet each retailer's unique needs. Some adaptive behaviors include conforming or changing approach based upon interactions with others or proposing solutions that are mutually beneficial to the people or organizations involved. Thus, by using technology to support adaptive behaviors, we propose:

H5. Holistic ST use relates positively to adaptive behaviors.

Technology enables a wide variety of presale planning activities. For example, ST can improve a salesperson's planning for a sales interaction by making tasks—such as managing promotion funds or forecasting sales—easier or more practical. During a sales interaction, IT can also improve the salesperson's capacity to access relevant information quickly and respond to buyer questions and objections. Therefore:

H6. Holistic ST use relates positively to planning.

4.5. *Purpose-specific technology use, working smarter, and key performance outcomes*

In a modern sales context, technology use matters. The most enlightened sales research explicitly models the effects of ST use on tasks and results. Technology use often centers on a holistic measure to test for hypothesized effects, and—given the literature's demonstrated relevance of use on countless sales behaviors and results in contemporary sales—a holistic ST use measure should be the minimal consideration when designing sales research. Such consideration helps avoid endogeneity concerns with model specifications by controlling for a relevant predictor. Nonetheless, as this research demonstrates, the practice of relying on a solely upon a holistic ST use measure can yield misleading statistical results.

Simply put, different individual technologies may serve different purposes—and different people can adapt their behaviors in different ways when using technology (Schmitz et al., 2016). Overlooking that reality may yield misleading results and false interpretations of effects relevant to technology use, which impedes both the sales science and practice. Thus, deciding on a suitable aggregation for measuring use is a central concern relevant to assessing returns.

There are intermediate purposes worth considering. Bakos and Treacy (1986) proposed three major uses of IT—storage, processing, and communication—while arguing that IT improves an organization's efficiency and effectiveness by reducing the otherwise adverse effects of bounded rationality. In the professional selling context, Hunter and Perreault (2007) build on Huber's (1991) and Sinkula's (1994) work to propose four purposes of IT use, while noting that storage would be antecedent to an application (i.e., its effects would occur after the user accessed that stored information). Processing capacity can be viewed as using technology for analyzing information. Thus, Hunter and Perreault (2007) propose three measures representing using technology for (1) accessing information, (2) analyzing information, and (3) communicating information. They defined *accessing* as a means of learning through knowledge acquisition; *analyzing and better understanding information* as a parallel to Huber's (1991) information interpretation; and *communicating* to capture Huber's (1991) learning concept of information distribution.

Of note, if measurement did not matter, the three purpose-specific uses (accessing, analyzing, and communicating) would all not yield differential effects on key sales behaviors (e.g., working smart) and outcomes (e.g., efficiency and effectiveness)—and the constructs would approach unity with the holistic ST use measure; that is, the four measures would lack discriminant validity. In particular, the accessing, analyzing, and communicating uses would not be distinct constructs—and all measures would be reflective of one another. Using a holistic ST use measure (direct) theorizes that the three different purposes are not relevant (or are too detailed) for inclusion in a study's model specification. Instead, if one measures the three purpose-specific uses, an empirical estimate of their explanatory power on a composite measure of holistic ST use (aggregated) indicates the extent to which the three measures capture holistic technology use (e.g., are a direct measure of holistic ST use). Thus, the extent to which each of these three measures of use impact a holistic (aggregated or direct) measure of technology use provides diagnostic value while also testing whether the underlying components (accessing, analyzing, and communicating) can provide additional insights in an ST use study. Such measures establish a proxy for the relative share of holistic use represented by each of these three purpose-specific uses. Moreover, these purpose-specific uses add specificity in defining the mechanisms through which ST may improve (or reduce) productivity (efficiency and effectiveness at the individual user level). Thus, these three types of use are distinguishable from ST holistic use (both aggregated and direct), although they serve as predictors for ST holistic use (aggregated).

H7. Using technology for accessing, analyzing, and communicating information represent distinguishable measures of technology use which can function as reflective components of holistic technology use.

As previously argued, while a holistic use of technology measure should influence planning, not all types of use contribute to that effect. Accessing and analyzing information are key planning tasks aided by technology. However, using technology to communicate information to customers occurs after the planning process. Therefore:

H8. Using technology for accessing information positively relates to working smarter.

H9. Using technology for analyzing information positively relates to working smarter.

H10. Using technology for communicating information positively relates to working smarter.

While technology use drives returns on effectiveness by influencing other behaviors (e.g., working smarter or relationship-forging behaviors), IT use should have a direct and positive effect on administrative efficiency (Hunter & Perreault, 2006). Similarly, administrative efficiency gains will be realized across all three different dimensions of use (accessing, analyzing, and communicating information) examined here. As an example, using technology to access information should improve a salesperson's capacity to be timely in completing administrative responsibilities. Thus,

H11. Using technology for accessing, analyzing, and communicating information relates positively to efficiency.

Not only will these different purposes of use relate differently to “working smart” tasks, they will also have positive effects on an individual's effectiveness.

H12. Using technology for accessing, analyzing, and communicating information relates positively to effectiveness.

4.6. *Using individual technology tools influences key sales behaviors and outcomes*

In contrast to conceptualizations using intermediate measures that group tools together (Zablah et al., 2012), this research proposes that using different technology tools will have different effects on the different purposes of use (accessing, analyzing, and communicating information) as well as the performance outcomes—and those effects can be related to the malleability or purpose-specific design of the individual technology.

H13. The effects of individual technologies on working smart and performance outcomes will be consistent with expectations for people to adapt use or tasks to ensure performance returns to the extent an IT is malleable to that purpose.

5. Research methods

5.1. Sample

This paper relies on data collected from two different host firms. In both cases, a preliminary questionnaire was developed, discussed, and refined using in-depth pre-test interviews with executives representing several different industries. After refining the survey instruments, pretests were completed to clarify items and ensure completeness. These were completed with help from managers within the host firms—well-respected and reputable consumer packaged goods firms.

For data collection, selection as a host firm (and, thus, the baseline conditions for generalizability of the results) included several conditions. First, their salespeople must conduct typical work tasks, including interactions with both internal and external contacts. Second, the firm must sell to businesses that characteristically involve a more rational decision making process. Third, IT tools, including both purpose-specific and malleable tools, must already be adopted by the company and be available to users. Fourth, the use of technology must be voluntary. Fifth, technology skills must vary across users. Sixth, the organization must be large enough to support statistical tests of the hypothesized relationships. Finally, the firm's management must agree to encourage participation and accept the research team's conditions for ensuring confidentiality of the respondents. Both firms requested totaled reporting of results (for example, cross-tabs and summaries of responses).

For both studies, the host firm allowed a survey of major divisions of its U.S.-based consumer packaged goods sales forces. First, before taking part, the firms sought and secured confidentiality agreements, which included anonymity in publishing the firm's participation. Second, the manager limited the time necessary to complete the survey. Third, the research team agreed to provide a descriptive report to management on the study's results. Fourth, the team included some questions—of interest to the approving managers—that were not part of this study. To improve response rates, both firms' top sales executive sent a pre-notification letter to each salesperson to encourage participation. This pre-notification letter was followed later with a cover letter, from the same executive, which introduced the questionnaire packet. The cover sheet of the questionnaire guaranteed each respondent's confidentiality. To further signal and improve anonymity of responses, questionnaires were sent to the users' home office addresses (as they worked from mobile arrangements) and completed questionnaires were returned directly to the research team. The two resulting survey instruments included both common and unique elements.

For the first study, of 85 questionnaires distributed, 79 were returned. Five respondents were dropped from the analysis based on missing data for one or more measures, yielding an effective response rate of 87% (74/85). Of the respondents, 80% were male, and 96% had attended college. For the second study, 134 responses were received from 176 questionnaires delivered. Due to missing data, three more were dropped, yielding an effective response rate of 74% (131/176). Again, consistent with the context, the respondents were predominantly male, and were college educated. The average age was 42 years old (range: 23–63 years old). Although the data are not pooled for the reported results, both studies are consistent with each other and with commonly reported baseline demographics for B2B sales forces working in the United States.

5.2. Measurement

Table 1 shows the scale items and reliabilities for both studies.

Scales measuring efficiency and effectiveness are consistent with those used in the B2B sales literature and are based on a subset of self-report performance items adapted from Behrman and Perreault (1982). Each respondent was asked to rate each item on "how well you have performed relative to an average salesperson in similar selling situations" with a seven-point scale anchored by "needs improvement" (1) and "outstanding" (7).

The proposed measure of holistic technology use is adapted from (Hunter & Perreault, 2006) to fit the more general definition of holistic ST use defined in this research. The holistic use measure is based on eight Likert-type items on a seven-point scale anchored by "strongly disagree" (1) and "strongly agree" (7). The purpose-specific measures of technology uses were adapted from Hunter and Perreault's (2007) bipolar adjective scales assessing the extent to which users consider their use as routine, frequent, and emphasized along the three purpose-specific uses of accessing, analyzing, and communicating information.

For the first study, the planning measure was adapted from a 12-item scale developed by Sujan et al. (1994). In the second study, the measure used for market-driven sales planning was adapted from the extant literature and is more specific to how salespeople use technology to gain insights from market data (Hunter, 2014). To measure adaptive behavior, in the first study, the "practicing adaptive selling" measure is a shorter version (four items) of the scale proposed by Spiro and Weitz (1990). Finally, in the second study—again, to be more specific about how technology could be used in an adaptive way—the scale for proposing mutually-beneficial ideas was adapted from Hunter and Perreault's (2007) scale for proposing integrative solutions. All four of these scales for measuring dimensions of working smarter in a sales context used seven-point Likert-type items anchored by "strongly disagree" (1) and "strongly agree" (7).

Finally, to measure disaggregated use at the technology tool level, users were asked to indicate, using a seven-point Likert scale (anchors were "not at all" [1] and "very heavily" [7]), the extent of his or her use of each of several different hardware and software tools.

5.3. Data analysis

As the hypotheses are not causal, but instead correlational, analysis of the data involved first establishing the validity and reliability of the constructs, and then testing for statistically significant product-moment correlations across the tools and constructs.

As the number of parameters required to estimate all items in a single Confirmatory Factor Analysis (CFA) model exceeds the observations available in either study, two separate CFA measurement models were specified and tested. To provide the most conservative test of validity and reliability, two models were estimated. The first CFA model included the working smart constructs (planning and adaptive behaviors) and the performance outcomes (efficiency and effectiveness). The second CFA model included the four latent constructs measuring technology uses (holistic technology use and the three purpose-specific uses—accessing, analyzing, and communicating).

Jöreskog and Sörbom (2001) recommend using structural equation modeling (SEM) with maximum likelihood parameter estimation to assess the psychometric properties of measures. In addition, Fan and Wang (1998) suggest using overall fit measures that are robust to small samples, focusing fit criteria on the Comparative Fit Index (CFI) and Incremental Fit Index (IFI). Also, as far as relying on the CFI and IFI, this work follows the practice of other SEM research in reporting the χ^2 statistics with its degrees of freedom and the Goodness of Fit Index (GFI) for both CFA models.

6. Results

Table 1 summarizes the survey instruments and overall fit statistics for the constructs used in these studies. Data from the second study were used as it included more of both items and scales best suited for the contributions of this work. Using Bollen's (1989) guidelines for

Table 1
Summary of scale statistics for survey instruments.

Construct Name Items for Construct	Reliability Study 1 [Study 2]	CFA loading Study 2 Only	*P*-value
PROCESS OUTCOMES			
Effectiveness (*External*) (adapted from Behrman & Perreault, 1982); **AVE = 0.65**	0.86 [0.84]		
Listening attentively to identify and understand the real concerns of your customers.		0.84	(< 0.001)
Working out solutions to a customer's questions or objections.		0.82	(< 0.001)
Convincing customers that I understand their unique problems and concerns.		0.76	(< 0.001)
Efficiency (*Internal*) (adapted from Behrman & Perreault, 1982); **AVE = 0.63**	0.72 [0.80]		
Submitting required reports on time.		0.93	(< 0.001)
Addressing my administrative responsibilities in a timely manner.		0.88	(< 0.001)
Producing accurate and complete records and reports.		0.51	(< 0.001)
ST USES			
Holistic ST Use (*Direct Measure*) (adapted from Hunter & Perreault, 2006); **AVE = 0.46**	0.74 [0.72]		
Compared to others in sales, I'm technology oriented.		0.69	(< 0.001)
I extensively use information technology to perform my job.		0.67	(< 0.001)
I try to link different sales technologies so that they work together well.		0.67	(< 0.001)
Intermediate* (*Purpose-specific*) *ST Use (adapted from Hunter & Perreault, 2007)			
Using [sales] technology to **access** information; **AVE = 0.76**	[0.89]		
"routine" to "sporadic"		0.94	(< 0.001)
"frequent" to "infrequent"		0.81	(< 0.001)
"a major emphasis" to "not a major emphasis"		0.86	(< 0.001)
Using [sales] technology to **analyze** information; **AVE = 0.85**	[0.94]		
"routine" to "sporadic"		0.92	(< 0.001)
"frequent" to "infrequent"		0.91	(< 0.001)
"a major emphasis" to "not a major emphasis"		0.93	(< 0.001)
Using [sales] technology to **communicate** information; **AVE = 0.83**	[0.93]		
"routine" to "sporadic"		0.91	(< 0.001)
"frequent" to "infrequent"		0.95	(< 0.001)
"a major emphasis" to "not a major emphasis"		0.87	(< 0.001)
Individual Tool (*Disaggregated*) *ST Use* (*see* Table 2)WORKING SMARTER/RELATIONSHIP-FORGING TASKS			
Planning for the Sale (Study 1; Sujan et al., 1994)	0.78	N/A	
I set personal goals for each sales call.			
I think about strategies I will fall back on if problems in a sales interaction arise.			
I am careful to work on the highest priority tasks first.			
Each week I make a plan for what I need to do.			
I keep good records about my account(s).			
Market-driven Sales Planning (Study 2; adapted from Hunter, 2014); AVE = 0.64	[0.85]		
I evaluate the specific information needs of the buyer I will be meeting.		0.92	(< 0.001)
I collect information that will forewarn me of possible problems with the account.		0.74	(< 0.001)
I plan my presentation to respond to objections I anticipate from the buyer.		0.72	(< 0.001)
Adaptive Selling (Study 1; Spiro & Weitz, 1990)	0.74	N/A	
I can easily use a wide variety of selling approaches.			
I vary my sales style from situation to situation.			
I feel that most buyers can be dealt with in pretty much the same manner.			
I treat all buyers pretty much the same.			
Proposing Mutually-beneficial Ideas (adapted from Hunter & Perreault, 2007); **AVE = 0.53**	[0.77]		
I'm good at finding opportunities that benefit both my firm and my customers.		0.80	(< 0.001)
I try to solve customer problems in ways that also help my firm.		0.69	(< 0.001)
I look for good ways to integrate my customer's goals with my company's needs.		0.69	(< 0.001)

overall fit assessment, the first CFA model—including the efficiency, effectiveness, and working smart constructs—produced an adequate overall fit (GFI = 0.90, IFI = 0.95, CFI = 0.95, RMSEA = 0.08), although the chi-square statistic is statistically significant ($\chi^2 = 87.7$, df = 48 $p. < 0.05$). Similarly, the second CFA model—including the four latent measures of technology use constructs—produced an adequate overall fit (GFI = 0.92, IFI = 0.97, CFI = 0.97, RMSEA = 0.07), although the chi-square statistic is statistically significant ($\chi^2 = 79.6$, df = 48 $p. < 0.05$). Item reliabilities were assessed using the resulting loading for each item and are reported in Table 1. All item reliabilities are statistically significant ($p. < 0.01$).

Table 2 summarizes the results from Study 1. Table 3 summarizes findings from Study 2.

6.1. Holistic technology use and outcomes

Consistent with **H1**, **H2**, and the underlying theory that technology use improves both efficiency and effectiveness, the results of Study 2 are supportive of both hypotheses, with positive and statistically significant Pearson correlations ($\beta = 0.18$ and.29, respectively).[1] However, in the first study, holistic technology use relates positively to efficiency only ($\beta = 0.26$, $p. < 0.05$), and not to effectiveness ($\beta = 0.07$, $p. = 0.56$). Thus, consistent with the logic of SFA and most research on technology use, this paper provides evidence that technology use improves the user's efficiency. On the other hand, the two studies are equivocal on confirming a positive effect of technology use on effectiveness—and **H2** is only partially supported.

6.2. Working smart and outcomes

The effects of working smart on efficiency and effectiveness are not the focal element of this research but do provide evidence that helps validate this research. Consistent with **H3 and H4**, the two working smarter behaviors (adaptive behaviors and planning) relate positively to efficiency and effectiveness—and all four effects are statistically significant, as shown in Table 2, for these relationships.

[1] Standardized Ordinary Least Squares (OLS) beta coefficients (Pearson correlations) are reported and thus the β symbol is adopted for brevity.

Table 2
Summary of OLS simple regression results for Study 1[a].

	Means and variances		Age	Holistic ST use	Performance outcomes		Working smarter	
	Mean	Std. dev.	Age	Holistic ST use	Effeciency	Effectiveness	Adaptive selling	Planning
Age (categorial measure)	n/a	n/a	1					
Holistic ST use-direct (H1 & H2)	4.76	1.03	−0.23**	1				
Efficiency (H3 & H4)	5.79	0.93	0.07	0.26**	1			
Effectiveness (H3 & H4)	5.65	0.76	−0.08	0.07	0.13	1		
Adaptive Selling (H5)	5.38	0.92	−0.04	0.26**	0.13	0.29**	1	
Planning (H6)	5.72	0.82	−0.14	0.39**	0.34**	0.31**	0.21*	1
Purpose-specific tools (H13)								
Order status software	5.59	1.99	−0.22*	0.02	0.31**	0.17	0.09	0.23**
Promotion funds software	5.19	2.15	0.02	0.13	0.23**	0.29**	0.07	0.10
Order entry software	4.67	2.46	−0.23**	0.11	0.21*	0.03	−0.02	0.12
Contact mgmt. software	3.80	2.01	−0.43**	0.16	0.18	0.21*	0.08	0.09
Time management software	3.52	2.08	−0.23**	0.02	0.14	0.18	0.01	−0.10
Shelf space mgmt. software	3.39	2.23	−0.37**	0.24**	0.40**	0.19*	0.38*	0.29**
Malleable tools (H13)								
E-mail	6.49	1.02	−0.11	0.19*	0.12	0.18	0.21*	0.06
Spreadsheet (e.g., Excel®)	5.04	1.86	−0.38**	0.44**	0.16	0.13	0.02	0.12
Graphics (e.g., PowerPoint®)	4.89	1.66	−0.36**	0.36**	0.14	0.16	0.13	0.18
Database software	4.14	1.95	−0.30**	0.21*	0.20*	0.22*	0.02	0.25**
Cell phone	2.65	1.84	−0.33**	0.06	−0.01	−0.05	0.04	0.08

[a] For Study 1, a single asterisk (*) indicates standardized OLS beta coefficients equal to or > 0.19 in magnitude, which results in a statistically significant two-tailed t-test (probability less than or equal to 0.10) and are shown in the table in ***bold italic*** face. This would be a $p < .05$ for a directional (positive or negative) one-tailed *t*-test. For an exploratory hypothesis, a double asterisk (**) indicates a beta coefficient equal to or > 0.23, representing a statistically significant two-tailed t-test at the p. < 0.05 level. For this study, as age was measured as an ordinal variable, its reported correlations are Spearman correlations.

Table 3
Summary of OLS simple regression results for Study 2[a].

	Means and variances		Holistic ST use	Intermediate level use measures		Working smarter/relationship-forging tasks			Sales performance	
	Mean	Std. dev.	Holistic ST use	ST use for access	ST use for analysis	ST Use for communicating	Sales planning	Mutually-beneficial proposals	Effeciency	Effectiveness
Construct-level effects										
Holistic ST use-direct	4.19	1.17	1							
ST use for accessing	4.58	1.48	0.44**	1						
ST use for analyzing	3.98	1.46	0.50**	0.57**	1					
ST use for communicating	4.97	1.48	0.53**	0.39**	0.35**	1				
Sales planning (H8, H9, H10)	4.76	0.95	0.34**	0.21**	0.28**	0.19**	1			
Proposing mutually-beneficial solutions (H8, H9, H10)	5.59	0.91	0.36**	0.15*	0.24**	0.33**	0.42**	1		
Efficiency (H11)	5.64	1.08	0.29**	0.24**	0.08	0.29**	0.36**	0.44**	1	
Effectiveness (H12)	5.59	1.00	0.18*	0.07	0.04	0.20**	0.46**	0.55**	0.53**	1
Age (years)	42.8	8.95	−0.19**	−0.15*	−0.10	−0.05	−0.03	−0.19**	0.07	0.16*
Purpose-specific software (H13)										
Order status software	3.05	2.13	0.10	0.31**	0.25**	0.04	0.00	0.13	0.12	0.13
Promotion funds software	3.65	2.62	0.17*	0.36**	0.37**	0.09	0.09	0.05	0.05	−0.04
Order entry software	2.16	1.75	0.01	0.16*	0.15*	−0.05	−0.02	0.11	0.02	0.11
Contact mgmt. Software	3.89	2.01	0.33**	0.30**	0.41**	0.27**	0.25**	0.27**	0.21**	0.22**
Time management software	3.13	2.06	0.21**	0.25**	0.23**	0.23**	0.13	0.15*	0.11	0.05
Shelf space mgmt. Software	2.62	2.03	0.17*	0.24**	0.28**	0.08	0.08	0.11	0.06	0.02
Malleable tools (H13)										
E-mail	6.31	1.38	0.15**	0.12	0.10	0.25**	0.08	0.15*	0.21**	0.06
Spreadsheet (e.g., Excel®)	4.87	2.05	0.28**	0.34**	0.38**	0.31**	0.15*	0.12	0.13	0.07
Graphics (e.g., PowerPoint®)	4.88	1.89	0.35**	0.40**	0.27**	0.36**	0.18*	0.15*	0.15*	0.11
Database software	4.22	2.14	0.25**	0.25**	0.35**	0.23**	0.10	0.15*	0.10	0.08
Cell phone	2.31	1.78	0.07	0.12	0.19**	0.05	0.07	0.09	−0.16*	−0.03

[a] For Study 2, a single asterisk (*) indicates standardized OLS beta coefficients equal to or > 0.15 in magnitude, which results in a statistically significant two-tailed t-test (probability less than or equal to 0.10) and are shown in the table in ***bold italic*** face. This would be a $p < .05$ for a directional (positive or negative) one-tailed t-test. For an exploratory hypothesis, a double asterisk (**) indicates a beta coefficient equal to or > 0.19, representing a statistically significant two-tailed t-test at the p. < 0.05 level.

6.3. Holistic technology use and working smart

Consistent with **H5**, holistic technology use positively affects planning, in both studies (β = 0.39 and 0.34, respectively). Also, as predicted by **H6**, holistic technology use positively influences adaptive behaviors (adaptive selling for Study 1 and proposing mutually beneficial ideas for Study 2), in both studies—with statistically significant effects (β = 0.39 and.34, respectively).

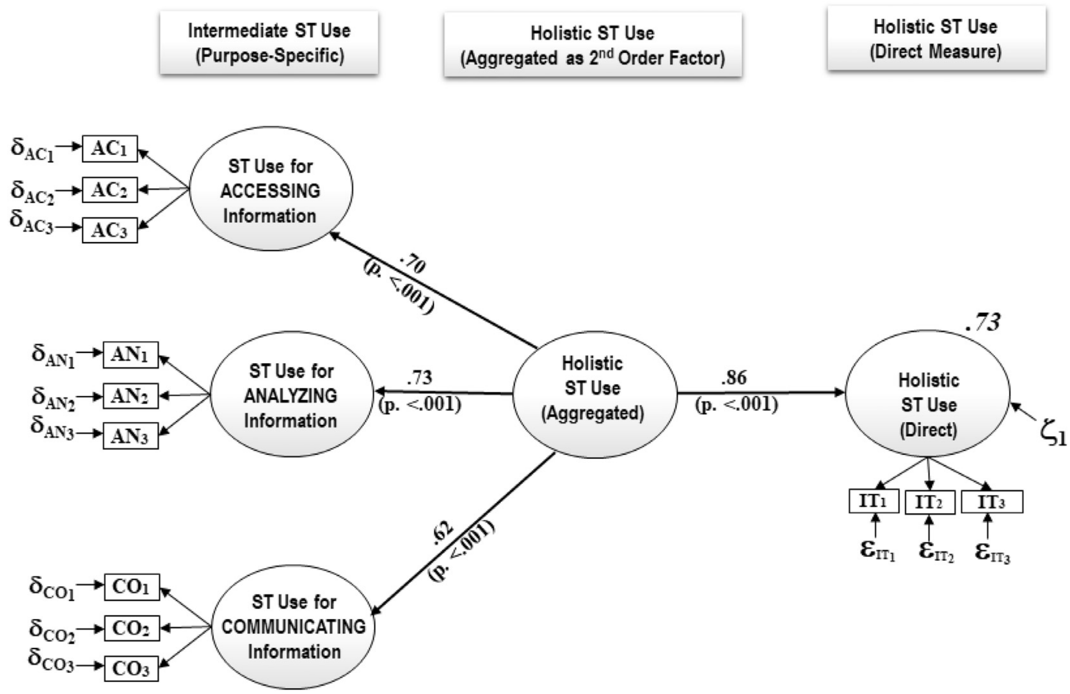

Fig. 2. Second-order ST use factor model showing an aggregated latent measure of ST relates to a direct self-report measure of holistic ST use.

6.4. Purpose-specific technology uses as distinct components of technology use

Fig. 2 shows the structural equation model specification used to test H7. As noted earlier, a measurement model with the four measures of technology use showed acceptable fit. To test H7, two structural equation model specifications were used. First, a model was tested that specified the three purpose-specific uses as dimensions of a higher order latent factor. The second-order model produced an adequate overall fit ($\chi^2 = 44.1$, df = 24, p. < 0.01, GFI = 0.94, IFI = 0.98, CFI = 0.98, RMSEA = 0.08). Loadings for each item reflect those reported from the earlier CFA measurement model, and correlations among the three factors are as follows: analyze to access (0.59), access to communicate (0.41), and analyze to communicate (0.37). The second structural model specification extended this second-order factor as a predictor of the measure of holistic technology use, and exhibits adequate fit ($\chi^2 = 91.4$, df = 28, p. < 0.01, GFI = 0.91, IFI = 0.97, CFI = 0.96, RMSEA = 0.08). These findings support H7, indicating that the three purpose-specific measures are reflective indicators (components) of a holistic measure of technology use. A major implication is that these purpose-specific measures do not function as reflective indicators (i.e. they are not interchangeable) of holistic technology use. Instead, each construct has its own meaning and measurement—and effects on other variables may differ. It's worth noting that a major advantage these measures afford is that each provides a more detailed account of how technology use impacts behavioral tasks and other outcomes (desirable or non-desirable consequences of each type of use).

6.5. Purpose-specific technology uses and working smart

Consistent with H8, H9, and H10, and as reported in Table 3, all three types of use have positive effects on the working smarter constructs. This study finds that accessing, analyzing, and communicating information positively relate to market-oriented sales planning ($\beta = 0.21$, 0.28, and 0.19, respectively) and the adaptive behavior of proposing mutually-beneficial ideas ($\beta = 0.15$, 0.24, and 0.33, respectively). Interestingly, while using technology to access information has the most positive relationship on sales planning, using technology for communicating information has the larger correlation with proposing mutually-beneficial ideas. While the holistic use measure indicates a positive correlation with both planning and adaptive proposals, it provides less insight than do the intermediate uses.

6.6. Purpose-specific technology uses and outcomes

Consistent with H11 and H12, using technology to access and communicate information are positively related to efficiency, whereas using technology to analyze information is not related to efficiency. Specifically, the findings support the view that, while using technology for accessing and communicating information is positively correlated with efficiency ($\beta = 0.24$ and 0.29, respectively), using technology for analyzing information is not positively related ($\beta = 0.08$). On the other hand, using technology ONLY to communicate information is positively related to effectiveness ($\beta = 0.19$). Collectively, these patterns of correlations indicate that findings differ depending on which definition, construct, and measure of technology use a researcher employs.

6.7. Correlations among use of technology tools and other constructs

To provide a richer view of how specific technologies relate to the tasks and outcomes investigated in these two studies, Table 2 and Table 3 show the mean and standard deviation of the respondents' uses for a variety of specific software and hardware tools. Given recent interests in how non-technical users employ malleable tools, these tables are further broken down into malleable and purpose-specific tools. The tables also provide bivariate correlations between each of the tools, the three purpose-specific uses, holistic technology use, the working smarter/relationship-forging tasks constructs, and the performance outcomes (efficiency and effectiveness).

7. Implications and limitations

This research has several implications for scholars and managers and some limitations.

7.1. Scholarly implications

The study demonstrates that scholars must follow traditional guidelines for using valid measures, including precision in construct definition, to make meaningful contributions to ST research. Study designs may begin with an understanding of the stark differences between automation strategies and augmentation strategies. In automation strategies, firms seek to employ ST tools to displace the work done by salespeople; that is, they seek to automate the performance of sales tasks. Ongoing acceleration of innovations in artificial intelligence and machine learning will automate many of the sales tasks performed by salespeople today (especially those that are routine and predictable, such as route planning, order placement for routine purchases, canned presentations delivered by salespeople, and so on). However, as the primary value added by professional selling remains two-way, person-to-person communications (either via technology or face-to-face), research into how salespeople can use ST tools to augment (facilitate or enable) their performance of sales tasks will remain a priority investment for sales organizations—and thus an ongoing need for ST research, particularly in the augmentation space. Meanwhile, for routine sales tasks, IT scholars may become more valuable to sales organizations seeking insights on how to automate the selling function.

Consistent with several other studies on ST use, this study supports the view that ST use is relevant to predicting key sales relationship-building behaviors (e.g., adaptive selling, planning, proposing mutually-beneficial solutions, and so on) and key aspects of sales performance (e.g., internal or external, efficiency, or effectiveness). Thus, studies that predict sales performance without considering the effects of ST use may represent a mis-specified model (e.g., the omitted variable is ST use) and thus produce invalid results. Moreover, as omitted variable bias can impact parameter estimates, positively or negatively, the omission represents a concern that cannot be addressed after a study has been implemented.

The findings in this study note that interpretation of theoretically-derived parameter estimates warrant scrutiny with respect to the ST measures used. Different categories of measures (holistic, intermediate, and individual tool levels) produce significantly different parameter estimates, even at the bi-variate levels, for effects on sales behaviors and sales performance outcomes. Therefore, while some ST use measures may support given hypotheses, others may not, while others may fully refute the hypotheses (e.g., create statistically significant effects in the opposite direction from the theoretically-proposed direction). During study design phases, it is paramount for the researcher to develop insights on which level and type of ST use measure fits with the study's model specifications. In the event multiple types of measures may be relevant (e.g., have a statistically significant effect on an endogenous variable in the model specification), researchers may want to include, at minimum, the intermediate levels of ST use (e.g., accessing, analyzing, and communicating). After a study has been completed, those measures can provide a second-order measure for holistic ST use (aggregated) should that fit better with the study's hypotheses—and this study shows that the resulting holistic ST use measure (aggregated) is highly correlated to a holistic ST use (direct measure).

Interestingly—and supportive of many studies that have used holistic direct measures of ST use—while such measures do not allow as detailed of an understanding as do the intermediate ST use measures (accessing, analyzing, and communicating), this study's findings support the view that the measure proposed here is highly related to the intermediate ST uses and thus provides a significant control variable for studies in which a more nuanced understanding of ST use is not needed (e.g., when ST use should be included as a control variable for key sales behaviors and outcomes).

Finally, this study is among the first to test the relationships across a wide variety of individual tools, intermediate ST uses, and holistic ST uses. The study demonstrates that a focus on an individual ST tool (e.g., spreadsheet or social media platform) as the study's ST use measure does not compensate for an absence of a holistic ST use, or intermediate use, measure. For example, for a study hypothesizing that holistic ST use relates positively to sales planning (a somewhat intuitive relationship), it likely depends on how the salesperson uses sales technology to augment her work. In Study 1 (Table 2), only three ST tools relate positively to sales planning (order status, shelf space management, and database software). In Study 2 (Table 3), while holistic measures of ST use and all three intermediate ST use measures (accessing, analyzing, and communicating) relate positively to sales planning, again, only three ST tools relate positively to sales planning (contact management, spreadsheet, and graphics software). However, a study design that does not include measures at the disaggregated, functional, or individual tool level may provide limited insight into how salespeople, on average, may gain returns on planning from such ST use.

7.2. Managerial implications

In addition to these scholarly implications for the study of ST use, there are several managerial implications.

First, of note, the patterns of use of different tools—and their relationships with different tasks and outcomes—are not replicated across the two host organizations. This is particularly true as the research investigates individual technology tools. This may provide a strong indicator of the importance to managers with respect to effective management of the ST portfolio (e.g., procuring, training, securing commitment, and implementing ST tools effectively). It also shows that simply providing cell phones, a laptop, and a range of tools may not be enough for a firm to maintain its competitiveness—particularly in industries embracing ST. Prior ST research notes that a firm within an industry can elevate customer expectations for ST use (Hunter & Perreault, 2006), which may lead to wider-spread adoption of new innovations, which may be exemplified by widespread implementation of social media across B2B sales organizations (Agnihotri et al., 2016; Ogilvie et al., 2018).

Second, the holistic ST use measure shows significant correlations with many of the software and hardware technology tools, representing an excellent way for sales organizations to audit its returns from investments in specific tools, applications, or underlying functional options. However, for those ST tools not related to the holistic measures, managers should question the returns such tools are providing within their organization. For Study 1, the only purpose-specific tool positively related to holistic ST use is shelf space management software, whereas several malleable tools (all except the cell phone) positively related to holistic ST use. Moreover, in this firm, holistic use is not positively related to building effective relationships, except through its indirect effects on adaptive selling and planning. Thus, while ST use may positively influence key performance outcomes, the portfolio of technology tools represented may not be optimal—and that could be for several reasons noted concerning the antecedents of ST adoption (e.g., training, equipment) or even an aging sales force, as age has high negative correlations with almost all tools represented in the firm's ST portfolio. For Study 2, order status, order entry, and cell phones are the only individual technologies not positively correlated with holistic ST use, and thus they may not be major drivers of ST use for that firm. Moreover, Study 2 benefits from insights on the intermediate levels of use as the relationships between using ST for accessing, analyzing, and communicating information relate to key sales behaviors as well as the salesperson use of individual tools. By combining these empirical estimates with a richer understanding of the contingency effects within the firm, additional managerial insights may emerge—or they may suggest further exploration of ST use toward developing a better understanding of whether the firm is gaining desired returns from its portfolio of ST tools. Interestingly, for this firm, cell phone use is negatively related to internal administrative efficiency, while not contributing significantly to ST use for accessing or communicating information—which may indicate cell phones are not being used productively.

Third, Tables 2 and 3 show a broad pattern of negative correlations between age and specific technology use and are consistent with research and practical observations concerning generational gaps among users. For Study 1, this may represent a major concern for the organization—and its ST use—which could be related to proper training, or sales reps who have plateaued in their careers. For Study 2, age appears to be less of a concern for the organization, indicating they may have better managed the "generation gap" associated with ST use.

Fourth, interestingly, the selling smart constructs show some significant correlations with reliance on specific technologies. These correlations may suggest which technologies facilitate or enable selling smart activities in this firm. The holistic IT use measure is related to only one purpose-specific tool for the organization sampled in Study 1, whereas that measure relates to several of the tools (purpose-specific software and malleable tool uses) in the second host organization (Study 2).

Fifth, for Study 2, the firm appears to be getting returns across a broader spectrum of malleable tools than is the firm in Study 1. Such data could be useful in benchmarking use across teams within a large organization or perhaps across firms within the same industry—as is true for these two firms (both are large consumer packaged goods manufacturers). The patterns demonstrate that the measure of technology use matters as the patterns for individual technology tools reflect neither the purpose-specific uses nor the holistic measure of use.

7.3. Limitations

First, while this is the first study to publish the range and detail of ST use across holistic, intermediate, and individual tool (or functional) levels, any interpretation of these data is enriched by better insights into the contingency effects that produce the results. As such, and as is true with most sales research, the results may not generalize to all sales contexts. For example, not all B2B sales organizations sell to resellers; not all of those selling to resellers work from home offices; and not all are as mobile or technology-savvy as the organizations included in this study. Not all industries are as information-intensive as the consumer-packaged goods industry investigated herein—which may mean the effects of ST use are less pronounced. At the same time, when coupled with other studies on ST use, there are very few industries immune to the impact of information technology use on productivity—and, perhaps, even fewer considered outside the pending influences of automation through machine learning and artificial intelligence. Moreover, while the study has limitations, its central purpose—to demonstrate that conceptualization, measurement, and assessment matter—likely extends well beyond studies on ST use and into studies of general IT use.

8. Concluding remarks

The study's findings support the major thesis of this work: The type of use measured matters. Studies on sales technology use employ a range of different measures representing divergence in conceptualization, measurement, and ultimately the management implications associated with conflicting findings on key concerns such as whether a firm is getting its desired returns from its investments in technology tools. For the academic literature, some findings may the simple artifacts of researchers using different measures. Consequently, the state of sales technology research and practice warrants critical consideration on key concerns especially considering the billions of dollars currently being spent annually by sales organizations.

What is most evident is that precision in measurement with specificity in matching purposes warrants scholarly attention to detail. For too many years, scholars have interchanged measures of holistic, intermediate, and disaggregated levels of ST use. This research shows that any findings lacking clarity and specificity in conceptualization and measurement should be viewed with great skepticism prior to management implementations.

Sales technology is a promising domain for research and practice. This study found significant relationships among technology use, key sales tasks, and the universally desirable outcomes of efficiency and effectiveness. Technology use can improve the user's ability to work smarter, more efficiently, and more effectively. However, when a firm invests in technology it should consider the tasks through which it anticipates returns—and it can use an approach such as this for diagnostic assessments on intended behavioral returns. In doing so, firms may realize greater returns on their investments and better focus attention on optimal uses of technology with specificity in purpose.

The study also suggests that malleable uses of technology may result in returns above and beyond the specific purpose for which they may have been acquired. This may be particularly true for younger salespeople who are often more adept at merging tasks and tools in unique ways to yield desirable results. These findings beg consideration of tasks and tools—and how organizations can help their employees integrate tools into their work processes. Better understanding of some of the new tasks enabled by technology within a variety of work contexts would enrich our understanding of how to assess returns on technology.

The challenges of understanding the role and impact of ST use must be addressed through a more refined view of what "use" means. Technology use occurs in domains that represent expensive, difficult-to-manage, and fast-changing priorities for global firms. Toward providing more value to practice and science, this study provides an empirical basis that should help improve conceptualization, theory, and measurement in this arena. While this work demonstrates that descriptive research can help establish benchmarks, future research should build on insights from this work and its call for increased specificity in conceptualizing, measuring, and managing sales technology use.

References

Agnihotri, R., Dingus, R., Hu, M. Y., & Krush, M. T. (2016). Social media: Influencing customer satisfaction in B2B sales. *Industrial Marketing Management, 53*, 172–180. https://doi.org/10.1016/j.indmarman.2015.09.003.

Agnihotri, R., Gabler, C. B., Itani, O. S., Jaramillo, F., & Krush, M. T. (2017). Salesperson ambidexterity and customer satisfaction: Examining the role of customer demandingness, adaptive selling, and role conflict. *Journal of Personal Selling & Sales Management, 37*(1), 27–41. https://doi.org/10.1080/08853134.2016.1272053.

Agnihotri, R., Kothandaraman, P., Kashyap, R., & Singh, R. (2012). Bringing "social" into sales: The impact of salespeople's social media use on service behaviors and value creation. *Journal of Personal Selling & Sales Management, 32*(3), 333–348. https://doi.org/10.2753/pss0885-3134320304.

Agnihotri, R., Trainor, K. J., Itani, O. S., & Rodriguez, M. (2017). Examining the role of sales-based CRM technology and social media use on post-sale service behaviors in India. *Journal of Business Research, 81*, 144–154. https://doi.org/10.1016/j.jbusres.2017.08.021.

Ahearne, M., Jones, E., Rapp, A., & Mathieu, J. (2008). High touch through high tech: The impact of salesperson technology usage on sales performance via mediating mechanisms. *Management Science, 54*(4), 671–685. https://doi.org/10.1287/mnsc.1070.0783.

Aral, S., & Weill, P. (2007). IT assets, organizational capabilities, and firm performance: How resource allocations and organizational differences explain performance variation. *Organization Science, 18*(5), 763–780.

Bakos, J. Y., & Treacy, M. E. (1986). Information technology and corporate strategy: A research perspective. *MIS Quarterly, 10*(2), 107–119. https://doi.org/10.2307/249029.

Banker, R. D., Bardhan, I. R., Chang, H., & Lin, S. (2006). Plant information systems, manufacturing capabilities, and plant performance. *MIS Quarterly, 30*(2), 315–337.

Baumgartner, T., Hatami, H., & Valdivieso, M. (2016). Why salespeople need to develop 'machine intelligence. *Harvard Business Review, 10*, 1–5.

Beaudry, A., & Pinsonneault, A. (2005). Understanding user responses to information technology: A coping model of user adaptation. *MIS Quarterly, 29*(3), 493–524.

Behrman, D. N., & Perreault, W. D., Jr (1982). Measuring the performance of industrial salespersons. *Journal of Business Research, 10*(3), 355–370.

Bollen, K. A. (1989). *Structural equation modeling with latent variables.* New York: John Wiley & Sons.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* WW Norton & Company.

Clark, L. A., & Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment, 7*(3), 309.

Collins, R. H. (1985). Enhancing spreadsheets for increased productivity. *Journal of Personal Selling & Sales Management, 5*(2), 79–81.

Collopy, F. (1996). Biases in retrospective self-reports of time use: An empirical study of

computer users. Management Science, 42(5), 758–767.
Davenport, T. H., & Kirby, J. (2015). Beyond automation. Harvard Business Review, 93(6), 59–65.
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–339.
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.
DeSanctis, G., & Poole, M. S. (1994). Capturing the complexity in advanced technology use: Adaptive structuration theory. Organization Science, 5(2), 121–147. https://doi.org/10.1287/orsc.5.2.121.
Fan, X., & Wang, L. (1998). Effects of potential confounding factors on fit indices and parameter estimates for true and misspecified SEM models. Educational and Psychological Measurement, 58(5), 701–735.
Franke, G. R., & Park, J.-E. (2006). Salesperson adaptive selling behavior and customer orientation: A meta-analysis. Journal of Marketing Research, 43(4), 693–702. https://doi.org/10.3978/j.issn.2072-1439.2012.05.03.
Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. MIS Quarterly, 19(2), 213–236.
Gwin, J. M. (1979). The effect of the sales call planning process on the performance outcomes of commercial and industrial sales forces. PhD Doctoral dissertationChapel Hill, NC: University of North Carolina.
Gwin, J. M., & Perreault, W. D., Jr. (1981). Industrial sales call planning. Industrial Marketing Management, 10(3), 225–234. doi: https://doi.org/10.1016/0019-8501(81)90018-3.
Harrison, D. E., & Hair, J. F. (2017). The use of technology in direct-selling marketing channels: Digital avenues for dynamic growth. Journal of Marketing Channels, 24(1/2), 39–50. https://doi.org/10.1080/1046669X.2017.1346979.
Hu, Q., & Quan, J. J. (2005). Evaluating the impact of IT investments on productivity: A causal analysis at industry level. International Journal of Information Management, 25(1), 39–53. https://doi.org/10.1016/j.ijinfomgt.2004.10.006.
Huber, G. P. (1991). Organizational learning: The contributing processes and the literatures. Organizational Science, 2(February), 89–115.
Hunter, G. K. (2011). Sales technology. In D. W. Cravens, K. Le Meunier-FitzHugh, & N. Piercy (Eds.). Oxford handbook of strategic sales and sales management (pp. 426–457). Oxford: Oxford University Press.
Hunter, G. K. (2014). Customer business development: Identifying and responding to buyer-implied information preferences. Industrial Marketing Management, 43(7), 1204–1215. https://doi.org/10.1016/j.indmarman.2014.06.008.
Hunter, G. K., Bunn, M. D., & Perreault, W. D., Jr. (2006). Interrelationships among key aspects of the organizational procurement process. International Journal of Research in Marketing, 23(2), 155–170. doi: https://doi.org/10.1016/j.ijresmar.2005.10.001.
Hunter, G. K., & Panagopoulos, N. G. (2015). Commitment to technological change, sales force intelligence norms, and salesperson key outcomes. Industrial Marketing Management, 50(10), 162–179. https://doi.org/10.1016/j.indmarman.2015.03.023.
Hunter, G. K., & Perreault, W. D., Jr. (2006). Sales technology orientation, information effectiveness, and sales performance. Journal of Personal Selling & Sales Management, 26(2), 95–113.
Hunter, G. K., & Perreault, W. D., Jr. (2007). Making sales technology effective. Journal of Marketing, 71(1), 16–34. doi: https://doi.org/10.1509/jmkg.71.1.016.
Jelinek, R. (2013). All pain, no gain? Why adopting sales force automation tools is insufficient for performance improvement. Business Horizons, 56(5), 635–642. https://doi.org/10.1016/j.bushor.2013.06.002.
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. https://doi.org/10.1080/08853134.2002.10754303.
Jöreskog, K. G., & Sörbom, D. (2001). LISREL 8.50: User's reference guide B2 - LISREL 8.50: User's reference guide. Chicago: Scientific Software International.
Kumar, V. (2015). Evolution of marketing as a discipline: What has happened and what to look out for. Journal of Marketing, 79(1), 1–9. https://doi.org/10.1509/jm.79.1.1.
Lacoste, S. (2016). Perspectives on social media ant its use by key account managers. Industrial Marketing Management, 54, 33–43.
Limbu, Y. B., Jayachandran, C., & Babin, B. J. (2014). Does information and communication technology improve job satisfaction? The moderating role of sales technology orientation. Industrial Marketing Management, 43(7), 1236–1245. https://doi.org/10.1016/j.indmarman.2014.06.013.
Mithas, S., Krishnan, M. S., & Fornell, C. (2005). Why do customer relationship management applications affect customer satisfaction? Journal of Marketing, 69(4), 201–209.
Mithas, S., Tafti, A., Bardhan, I., & Mein Goh, J. (2012). Information technology and firm profitability: Mechanisms and emperical evidence. MIS Quarterly, 36(1), 205–224.
Ogilvie, J., Agnihotri, R., Rapp, A., & Trainor, K. (2018). Social media technology use and salesperson performance: A two study examination of the role of salesperson behaviors, characteristics. and training. Industrial Marketing Management, 75(11), 55–65. https://doi.org/10.1016/j.indmarman.2018.03.007.
Onyemah, V., Swain, S. D., & Hanna, R. (2010). A social learning perspective on sales technology usage: Preliminary evidence from an emerging economy. Journal of Personal Selling & Sales Management, 30(2), 131–142. https://doi.org/10.2753/pss0885-3134300204.
Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. Human Factors, 39(2).
Rangarajan, D., Chonko, L. B., Jones, E., & Roberts, J. A. (2004). Organizational variables, sales force perceptions of readiness for change, learning, and performance among boundary-spanning teams: A conceptual framework and propositions for research. Industrial Marketing Management, 33(4), 289–305. https://doi.org/10.1016/s0019-8501(03)00072-5.
Rapp, A., Agnihotri, R., & Forbes, L. P. (2008). The sales force technology-performance chain: The role of adaptive selling and effort. Journal of Personal Selling & Sales Management, 28(4), 335–350. https://doi.org/10.2753/PSS0885-3134280401.
Rapp, A., Beitelspacher, L. S., Schillewaert, N., & Baker, T. L. (2012). The differing effects of technology on inside vs. outside sales forces to facilitate enhanced customer orientation and interfunctional coordination. Journal of Business Research, 65(7), 929–936. https://doi.org/10.1016/j.jbusres.2011.05.005.
Rapp, A., Trainor, K. J., & Agnihotri, R. (2010). Performance implications of customer-linking capabilities: Examining the complementary role of customer orientation and CRM technology. Journal of Business Research, 63(11), 1229–1236. https://doi.org/10.1016/j.jbusres.2009.11.002.
Ray, G., Muhanna, W. A., & Barney, J. B. (2005). Information technology and the performance of the customer service process: A resource-based analysis. MIS Quarterly, 29(4), 625–652.
Roach, S. S. (1987). America's technology dilemma: A profile of the information economy. Morgan Stanley.
Schillewaert, N., Ahearne, M. J., Frambach, R. T., & Moenaert, R. K. (2005). The adoption of information technology in the sales force. Industrial Marketing Management, 34(4), 323–336. https://doi.org/10.1016/j.indmarman.2004.09.013.
Schmitz, K. W., Teng, J. T., & Webb, K. J. (2016). Capturing the complexity of malleable IT use: Adaptive structuration theory for individuals. MIS Quarterly, 40(3), 663–686.
Schrock, W. A., Zhao, Y., Hughes, D. E., & Richards, K. A. (2016). JPSSM since the beginning: Intellectual cornerstones, knowledge structure, and thematic developments. Journal of Personal Selling & Sales Management, 36(4), 321–343. https://doi.org/10.1080/08853134.2016.1253019.
Sharma, A., & Sheth, J. N. (2010). A framework of technology mediation in conusmer selling: Impications for firms and sales management. Journal of Personal Selling & Sales Management, 30(2), 121–129.
Sinkula, J. M. (1994). Market information processing and organizational learning. Journal of Marketing, 58(1), 35–45.
Speier, C., & Venkatesh, V. (2002). The hidden minefields in the adoption of sales force automation technologies. Journal of Marketing, 66(3), 98–111. https://doi.org/10.1509/jmkg.66.3.98.18510.
Spiro, R. L., & Weitz, B. A. (1990). Adaptive selling: Conceptualization, measurement, and nomological validity. Journal of Marketing Research, 27(1), 61–69.
Sujan, H. (1986). Smarter versus harder: An exploratory attributional analysis of salespeople's motivation. Journal of Marketing Research, 23(1), 41–49. https://doi.org/10.2307/3151775.
Sujan, H., Sujan, M., & Bettman, J. (1988). Knowledge structure differences between more effective and less effective salespeople. Journal of Marketing Research, 25(1), 81–86.
Sujan, H., Weitz, B. A., & Kumar, N. (1994). Learning orientation, working smart, and effective selling. Journal of Marketing, 58(3), 39–52.
Sundaram, S., Schwarz, A., Jones, E., & Chin, W. W. (2007). Technology use on the front line: How information technology enhances individual performance. Journal of the Academy of Marketing Science, 35(1), 101–112. https://doi.org/10.1007/s11747-006-0010-4.
Tanner, J. F., Jr., Ahearne, M., Leigh, T. W., Mason, C. H., & Moncrief, W. C. (2005). CRM in sales-intensive organizations: A review and future directions. Journal of Personal Selling & Sales Management, 25(2), 169–180. https://doi.org/10.1124/dmd.108.022558.
Trainor, K. J., Andzulis, J. M., Rapp, A., & Agnihotri, R. (2014). Social media technology usage and customer relationship performance: A capabilities-based examination of social CRM. Journal of Business Research, 67(6), 1201–1208.
Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(February), 186–204.
Wang, G., Dou, W., & Zhou, N. (2012). The interactive effects of sales force controls on salespeople behaviors and customer outcomes. Journal of Personal Selling & Sales Management, 32(2), 225–244.
Weiner, B. (1980). The role of affect in rational (attributional) approaches to human motivation. Educational Researcher, 9(7), 4–11. https://doi.org/10.3102/0013189x009007004.
Zablah, A. R., Bellenger, D. N., Straub, D. W., & Johnston, W. J. (2012). Performance implications of CRM technology use: A multilevel field study of business customers and their providers in the telecommunications industry. Information Systems Research, 23(2), 418–435. https://doi.org/10.1287/isre.1120.0419.

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