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Sales Technology: A Three-Part Multi-Method Approach to Examining Sales-Stacks

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SALES TECHNOLOGY: A THREE-PART MULTI-METHOD APPROACH TO EXAMINING SALES-STACKS

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ABSTRACT

Salespeople depend on sales-related technologies to make themselves more efficient and effective. The extant sales-technology research tends to examine specific sales technologies in sales settings with the emphasis on the impact on salespeople. With the growth of technological capabilities, sales technology has become more integrated, thus making it harder to separate individual technologies from one another. The current research conducts a typological literature review of sales technology. Next, with an eye toward the development of indigenous theory, it introduces the term sales-stacks as capturing the aggregate of sales technologies that, when effective, provide a powerful, connected, easy-to-use experience for every sales role. Six foundational premises are introduced to differentiate sales-stacks from single use technology. Sequential chapters empirically test the proposed premises using nine unique samples, in a multistage, multi-method approach. Confirmatory factor analysis results, support the development of a three factor sales-stack effectiveness perceptions psychological measure. Nomological validity is then tested by employing the scale in a structural equation model with follow-up analyses using metric invariance testing. Findings support the positive relationship between perceptions of sales-stack effectiveness and salesperson outcomes. However, low sales-stack adopters make the relationship between sales-stack effectiveness and outcomes negative compared to their high adoption counter parts. Thus, sales managers need to make sure their organizational sales-stack is not only effective but also utilized to ensure salesforce success.

LIST OF ABBREVIATIONS AND SYMBOLS

API	Application Programing Interface
CFA	Confirmatory Factor Analysis
FP	Foundational Premise
PCA	Principal Component Analysis
SA	Sales technology (sales-stacks) adoption
ST	Sales Technology

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Introduction

According to Saleshacker.com the sales technology (ST) landscape has grown from 830 vendors to 950 in just twelve months (as of 2019). While 14% growth in new entrants does not raise much attention, acquisitions within the sales technology landscape have grown 250% to $9.5 billion and artificial intelligence is projected to grow 139% by 2022. Little debate exists among practitioners and scholars that the correct use of sales technology allows B2B organizations to make quicker, more informative, strategic decisions within their sales teams. However, when firms invest in ST based on the perceived shine of the technology rather than the overall functionality to the organization, it leaves the firm with very expensive and under-utilized technological tools. Furthermore, Cascio et al. (2010) finds that when there is an imbalance of support for ST from the sales leadership team, the entire organization may suffer from inefficiency of ST adoption. With so many ST options, sales managers no longer ask if sales technologies are needed to support the team, but what is the correct "stack" (the total set of tools available to a salesperson) or make up of the sales technologies to successfully support the team?

Current academic literature does not acknowledge the term sales technology stack (sales-stack for short), but hubspot.com defines it as "the technology/software salespeople need to do their jobs and communicate effectively with prospects." Ringdna.com defines a sales-stack as a "cohesive platform that delivers a powerful easy-to-use experience for every sales role." With the fragmented nature of the ST landscape larger tech companies are diversifying their ST tools through acquisition and development to create premade stacks for firms to utilize. While acquisitions cut down on the time needed for firms to research each individual technology, careless acquisitions create the potential to add additional unneeded ST, or even counter-productive software into a sales team's workflow. The proposed classification of sales technologies helps determine the options firms have to streamline their sales workflow. Hunt (2002; p. 199) states, "Classification schemata play fundamental roles in the development of a discipline in the that they are the primary means for organizing phenomena into classes or groups that are amenable to systematic investigation and theory development." The current study, further looks at the impact each ST solution has on the sales team, allowing for firms to cherry pick the correct stack that will improve organizational well-being.

Contribution Potential

Researchers have identified the need to understand the impact that ST has on sales teams and their processes. Singh et al. (2019) splits the issues of digitization and artificial intelligence technologies within a sales context into individual and organizational issues; the two inputs flow into an overlapping inquiry of how sales professions and ST interact to make an impact on the internal and external organization. Furthermore, Singh et al (2019). identifies key questions that future sales researchers should prioritize. To mention a few specifically:

- "Will digital technologies diminish or amplify the role of sales profession in customer value creation?
- What sales skills will be in demand? What skills will be less relevant?"
- "Do salespeople create higher value for buyers if they are equipped with intelligence from digital technologies?"

While these are just a few of the key questions within the ST research agenda, the need to classify the types of technologies is ever more prevalent. Solidifying a classification fills the void that is needed to move research from a theoretical agenda to an empirically testable model. Hunt

(1983) notes that organizing phenomena into classifications is the initial step within theory development. By classifying the ST based on the applicable use within the sales team, this research contributes a major stepping stone in answering future research questions and advancing the development a of ST theory.

Background

Current literature differentiates sales technologies through the different ways in which they are used (Hunter 2019; Hunter & Perreault 2007). In a holistic approach, ST is differentiated by direct verses aggregated use. For example, is a single piece (direct) of ST aiding the sales force to make decisions, or are multiple pieces aggregated to sway strategic decisions? Specifically, a direct use would be a price sheet to tell a sales team at what price the product should be offered. An aggregate use would be when a software takes into consideration the stored inventory levels, cost, and competitive pricing in real time to optimize the retail price and maximize ROI. Alternatively, the notion of a sales-stack equates to an aggregate use as multiple pieces of technology are employed to facilitate the salesperson or team. Without an aggregate approach, sales teams would be wasting technological resources that could support their informative decision making (Hunter, 2019).

Another, more popular approach to differentiating sales technologies is the purpose specific approach. Huber (1991) molded this approach from the IT literature (Bakos and Treacy 1986). Huber (1991) categorizes sales technologies within four learning-related constructs: 1) knowledge acquisitions, 2) information distribution, 3) information interpretation and 4) organizational memory. Huber's classification was later molded into three measures that categorize sales technology uses: 1) accessing information, 2) analyzing information and 3) communicating information (Hunter and Perreault, 2007). In the latter approach, organizational memory is removed from a classification of ST to an antecedent. Hunter and Perreault (2007) make the argument that in order to access, analyze, and communicate the use of ST, an organization must first store the data. Therefore, it's not part of the use of technology but an upfront necessity in implementing ST. Hunter (2019) finds that accessing and analyzing information from ST can positively influence the efficiency of a sales force, while communicating ST positively impacts effectiveness. However, the Huber classification lacks the complexity to capture the innovativeness of the implemented sales technology. In other words, in Huber's approach he makes the case that organization learning is linear, in that an organization goes through each phase one at a time to make decisions. With the advancement of artificial intelligence organizations do not need to start at step one and continue through the process for decision making. ST has streamlined this process to continually learn and project their competitive landscape making quicker more informed decisions. The access, analyze, and communicate approach has been shown as an influential predictor of ST use; but it does not help firms decide which ST to implement. It simply shows that once ST is adopted within an organization an increase in efficiency and effectiveness can generally be expected (Hunter 2019).

Few studies look to classify ST based on the functionality of each tool (Zablah et al., 2012; Hunter, 2019). Originally ST was differentiated between interaction support tools and prioritization tools (Zablah et al., 2012). That is, does a technology help a firm prioritize which customer to go after in a B2B context or does it help the sales team interact with a current customer during the sales process? Later ST was differentiated as either a malleable tool or purpose-specific tool (Hunter, 2019). For example, can the ST tool be manipulated to support the sales team current need (malleable) or does it provide a single strategic use and cannot be altered from its current state. While these classifications touch on the functionality component of the ST, each lacks the complexity needed in the growing ST landscape. Assuming firms have the resources to invest in ST, they are not looking for a one or the other choice, but rather which functionality investment can yield the greatest impact to their sales team and cross-functional organization. In light of this growing concern the current research looks to alleviate the confusion of this “black box” and classify ST tools based on the *functionality* they can bring to the organization. Functionality is defined as the sum of roles or capabilities associated with ST that creates value for the organization.

Sales Technology Barriers of Adoption

Researchers and C-level executives see the benefits of ST adoption to increase productivity and grow profits. However, salespersons are not always on board for the adoption of new tools. Tracing back to the technology acceptance model (TAM), Davis (1985,1989), two perceptual characteristics that influence adoption of sales technology are identified: perceived usefulness and perceived ease of use. Put simply, salespeople will prefer technologies seen as useful and easy to use over those seen as not useful or not easy to use (Davis 1989). Later, Schillewaert et al (2005) uses TAM as a mediator to see how perceived usefulness and ease of use impacted adoption. Similar to Davis (1989), perceived usefulness has a larger impact on ST adoption than ease of use.

Salesforce’ resentment for the adoption of ST is split dichotomously into internal and external barriers (Buehrer, Senecal and Pullins, 2005; Parthasarthy and Sohi, 1997). Internal barriers are defined as the salesperson’s skillset that would deter them from catching on to a new technology. Some factors that fall into this category are the salesperson’s technological competence and reluctance to change. External barriers are based on the organizational capabilities to support a new technology. Examples of these would be the breadth of support that the IT team can provide or money required to acquire such technologies.

Jones, Sundaram, and Chin (2002) take a different approach; instead of looking at barriers of ST adoption, they look at the antecedents of behavioral intention and infusion. Jones et al. (2002) make the distinction that intention is whether the salesperson will use the technology implanted into the organization; while infusion measures the extent to which a salesperson does use a technology. Their research finds that perceived usefulness and compatibility impacts intentions, while personal innovations, attitude toward the new system, and facilitating conditions affect infusion. The majority of factors consist of internal barriers based on the autonomy of a salesperson's role. However, organizational barriers must first be overcome before internal barriers can be pragmatically entertained (Parthasarthy and Sohi, 1997).

Wright and Donaldson (2002) examine the ST adoption process in the United Kingdom's financial service market and find evidence that salespersons exaggerate the organizational barriers that arise when adopting ST, eventually hindering the advancement and success of the sales technology. That is, without the proper buy in from the organization, the ST will have a reduced impact than what is perceived. A follow up study by Donaldson and Wright (2004) expands on the notion that organizational barriers outweigh technological barriers by looking at the United Kingdom pharmaceutical industry. Donaldson and Wright (2004) suggest that organizational goals tend to be misconstrued under the premise that the new ST will ensure increased return. Data needed to achieve the set goals could be fragmented or unavailable causing the adopted technology to be underutilized. Proper alignment of internal and external barriers needs to be examined to ensure a seamless adoption within the organization.

Not only do barriers need to be mitigated in order to achieve the adoption of ST but these barriers need to be continually scrutinized to ensure the adopted technology is synching up to the organizational goals. Speier and Venkatesh (2002) suggest that immediately following ST training, salespeople are very optimistic and supportive of the adoption of the technology. However, six months following the new ST training, salespersons exhibit increased levels of dissatisfaction towards the new technology, higher levels of absenteeism from the technology, and amplified levels of voluntary turnover. Salespersons can see the benefits of what the new technology can bring when utilized properly. However, miscommunication of the new processes to implement the technology can hamper the effectiveness of the ST. Retention of ST is just as important of an aspect as the adoption of the technology to avoid wasted resources and missed goals.

While organizational culture plays a major role in the adoption, implementation and success of new ST, Morgan and Inks (2001) suggest four key factors that increase the adoption of ST: 1) accurate expectations 2) user influence 3) training 4) commitment from management. Accurate expectations can best be described as the alignment of goals and processes within the organization prior to the adoption of the technology. User influence allows for cross-functional teams to understand and voice concerns prior to the adoption. For example, Larpsiri and Speece (2004) find that customers like when sales automation can increase efficiency. However, they do not want to see automation replace the personal contact of a salesperson. Without the preemptive input from the sales team, sales force automation would harm the organization more than help. Training is not only needed when adopting ST, but continual training needs to be administered to ensure salespersons stays comfortable and motivated with the new processes. Lastly, commitment from management needs to ensure that the new ST is not only adopted but that goals are aligned from the top of the organization down (Donaldson and Wright, 2004). Barriers for the introduction of ST into an organization present a growing concern, but, with proper alignment and preemptive implementation strategies, barriers can be overcome.

Proposed Classifications of Sales Technology based on Functionality

Social media and eCommerce strategies have developed and expanded over the past decade both in practice and as a topic in the academic sales literature. Managers are realizing that customers want to interact with brands at their convenience, and to stay relevant in the minds of customers, brands need to be more accessible. Customer relationship management (CRM) systems use to be the main sales tool for managing a sales force. However, customer relationship management (CRM) budgets are getting spread thin with the continual introduction of more digital tool's managers continue to raise the question of where can firms get the best ROI within these tools (Hoffman and Fodor 2010). Based on the growing ST offerings in the marketplace and the increase in academic literature sales technologies tools can be divided into five functional areas:

1. Enablement Support

Enablement support tools are the bare minimum of what a salesperson needs to be successful in day-to-day operations. Enablement is an instrumental characteristic in that enablement makes something else useful happen. Tools that fall into the enablement category allow for all other technologies to be implemented and utilized. Enablement support tools can be defined as the hardware or software that supports salesperson's other tools but does not directly impact sales without other inputs. Tools that fall into this category would be hardware systems like tablets, computers, and cell phones. Simple software systems like Microsoft Excel, PowerPoint, and Outlook also fall into the enablement category. In all cases these tools do not aid the salesperson in strategic decision making but instead aid the salesperson in being efficient. These are the basic foundational tools that enable the salesperson to perform even the most basic job functions. The other categories that follow require enablement to be operational. The rest of the sales-stack build on the enablement tools.

Similar literature has identified enabler sales technologies as malleable technologies (Orlikowski, 1996). Authors define malleable as open-ended technologies that allow the user to improvise the use in order to achieve the desired results. Although malleable technologies are considered low cost, low risk implementations into an organization. Studies have found that organizations prefer more complex technologies to have improvisation capabilities as well (Elbanna 2006).

2. Customer Relationship Management

Customer Relationship management systems have been a staple for sales managers to track and forecast sales through their team. Prior research in customer relationship management (CRM) recognizes that to survive in the digital age contact points between the firm and the customer must provide value for both parties (Malthouse et al. 2013). However, introducing new technology into a firm is not a simple feat when processes are already in place. For firms to expand their CRM strategy into a social-CRM strategy, firms need to understand how new technologies can be integrated into their existing processes (Trainor et al. 2014). The challenge that firms and researchers are running into is with the introduction of the “social customers,” customer relationship management is taking on a new meaning (Peters et al. 2010).

As more firms grow their “social customer” base, practitioners and researchers need to reevaluate what customer relationship management means to their internal processes (Peters et al. 2010). Thus, with the expansion of more and more digital tools the definition of CRM is being elongated to umbrella new technological and social shifts (Trainor, 2012). This research adopts the definition of social customer relationship management as “the integration of traditional customer-facing activities, including processes, systems, and technologies, with emergent social media applications to engage customers in collaborative conversations and enhance customer relationships” (Trainor, 2012). As managers begin to understand the importance of moving towards a digital transformation of social CRM, it’s important that they focus on technologies that integrate with the currents systems to compliment the firm’s capabilities (Trainor 2014). The risk that firms run into when implementing social CRM is that they look at outputs (Facebook followers, obtained email addresses, Instagram reposts) rather than outcomes (ROI, gross margin, etc.). When a firm looks at outputs rather than outcomes, it can lead employees to make unprofitable and counterproductive decisions (Malthouse 2013). Similar to the argument that purchase intentions doesn't equate to purchase behavior (Morrison 1979), outputs (i.e., Facebook likes or adding leads to into a CRM system) do not mean there will be a future conversion into outcomes. ST tools allow for sales managers review team performance quicker and on a much granular level. However, if sales managers stress behavioral control on outputs within their team it can cause the sale force to put unnecessary emphasis on the outputs causing them to be unprofitable.

Pipeline management is no longer just organizing customers to ensure sales teams behavioral and performance goals are met; rather, pipeline management systems manage an organization's digital projects. Pipeline management systems are being adapted to not only track customers but coordinate new product launches, on-boarding progression and demand planning. Analytical algorithms within pipeline management systems allow for sales managers to assess, in real time, where their team's sales are currently rolling up to, as well as, future forecast based on the health and strategy of the company.

3. Market Intelligence

Organizational learning enables all functional areas of the organization to learn, develop and facilitate new ideas that can impact the direction of the organization (Hult et al. 2002). With eCommerce channels growing at an exponential rate, the opportunity to harvest sales data has seen complimentary growth. Based off the transparent nature of the eCommerce channel, salespersons have access to a much larger array of sales and market trends than in past decades. Collecting, analyzing and sharing market intelligence can improve the organizational learning between sales and marketing (Le Meunier-Fitzhugh and Piercy 2007).

Implementing systems that allow for inter-functional information exchanges can greatly improve bidirectional communications within the organization (Le Meunier-Fitzhugh and Piercy 2007). Le Meunier-Fitzhugh and Piercy (2007) find that market intelligence has a positive influence on collaboration, communication and organizational learning. However, market intelligence can only be a successful tool if the intelligence is shared between departments to ensure the information is focused on their customers (Kotler, Rackham, and Krishnaswamy 2006; Powell and Allgaier 1998).

Market intelligence is no longer looking at organizations POS and segmenting their customers based on there the largest potential basket size. With modern-day buyers comes modern-day solutions. Market intelligence has the capabilities to track buyers through every step of the buying process. Tactics such as looking at a buyer's time on page, or click path to see how they came to the product can all be collected and analyzed and turned into a sales plan. While, such technologies document past behavior. The data can feed into some other process by which it tries to predict future behavior (see automation tools). In a B2B context market intelligence allows for salespersons to gain further insights on the buyer and company to create a dossier of prospective clients helping build a competitive advantage.

4. Shared Technology

Web 2.0 displayed to firms selling physical products in physical stores, that they can no longer use the same strategies and tools when implementing selling strategies online. 79% of U.S. households shop online, which is up 22% from 2000 (Perez 2016). Shipping expectations have changed from 1-2 weeks to 1-2 hours. Sale associates are being replaced by online chat boxes. Window shopping has been replaced with a scroll bar and foot traffic has transitioned to web traffic. "As a result, web/ mobile channel startups can move forward at "internet speed," an impossibility with physical distributions and channels" (Blank and Dorf 2012; p. xxvii).

The landscape of how consumers shop has changed over the years. The sales process of how buyers and suppliers interact has adapted to those changes. Buyers and suppliers no longer interact based on the value proposition presented by the supplier, but rather, the interaction is defined by how well buyer-supplier supply chains coexist. An emerging process in the digital landscape is that sellers are enabling self-service increasingly through sophisticated buyer portals. Amazon requires suppliers to go through "Vendor Central," Wayfair requires suppliers to go through the "Wayfair Extranet and Walmart.com requires the use of "Supplier Center." The retailers require sellers to submit all required marketing copy to launch a product online through the portal. Upon being loaded into the portal the buyer has the opportunity to review the product to ensure the product fits their strategy.

Shared technology between a buyer and seller is the extent to which each side values the technology contributed to the relationship (Wilson 1995). The stronger the perceived value of the shared technology the stronger the commitment between the buyer and seller is forged. Shared technology must exist as suppliers and vendors develop strategic relationships to benefit their organizations (Powers and Reagan 2007). When building a sales-stack, it is imperative for organizations to not just look for technology that contributes to the success of their own organization but what can benefit their strategic partners and external supply chain.

5. Salesforce Automation

Automation tools can best be described as the use of information technology to support sales functions (Buttle Ang and Iriana 2006). On a surface level sales force automation (SFA) allows for organizations to collect, analyze and distribute data across all functional areas of an organization, without the need for additional head counts that it would take to do this process manually. Gronroos (2000) observes that the implementation of SFA allows for a mutually beneficial relationship with an organization's customers. Buttle et al. (2006) critiques the sales force automation literature and identifies five success factors of SFA: 1) Organizational/ Cultural 2) Projected-related 3) Inter-personal 4) Intra-personal 5) Technical.

The more complex the ST that is integrated into an organization, the more barriers can occur during the implementation phase of the ST. Introducing automated ST into an organization requires all internal and external systems to be cohesively connected to run properly. While this can be huge barrier for organizations to overcome; automation tools can be the competitive advantage needed to separate themselves from their competition. An overview of the five functional areas in sales technology can be seen in table 1.

Table 1. Sales technology functional classification

ST Dimension	Description of Sales Technology	Authors
Enablement Support	"An overarching dynamic capability that aligns varied firm resources to benefit the customer journey and selling productivity." (Peterson, Malshe, Friend, and Dover 2021)	Agnihotri et al. 2009; Dishman and Aytes 1996; Honeycutt et al. 1993; Lynch 1990
Sales Force Automation (SFA)	"By improving the speed and quality of information flow among the salesperson, customer and organization, SFA tools support the sales process" (Speier and Venkatesh 2002)	Agnihotri et al. 2009; Ahearne et al. 2008; Baker and Delpechitre 2013; Buehrer et al. 2005; Bush et al. 2007; Bush et al. 2010; Cascio et al. 2010; Dugan et al. 2020; Eggert and Serdaroglu 2011; Giovannetti et al. 2020; Homburg et al. 2010; Honeycutt 2005; Jelinek et al. 2006; Mahlamäki et al. 2020; Mallin et al. 2010
Customer Relationship Management (CRM)	"A tool to identify the most valuable clients, attract them as trusted clients, retain them with loyalty policies, and develop a lasting partnership with them, in this paper the following dimensions were used." (Guerola-Navarro, Gil-Gomez, Oltra-Badenes, and Sendra-García 2021; Ngai 2005)	Agnihotri et al. 2009; Ahearne et al. 2008; Buehrer et al. 2005; Bush et al. 2010; Dugan et al. 2020; Giovannetti et al. 2020; Harrison and Ajjan 2019; Itani et al. 2020; Moncrief 2015; Rodriguez and Trainor 2016; Rodriguez et al. 2018
Market Intelligence (MI)	"Gathering activities are defined as the acquisition of information regarding lead users, customers, competitors, and relevant publics" (Song and Thieme 2009)	Bush et al. 2010; Hunter and Panagopoulos 2015; Kuruzovich 2013; Limbu et al. 2014
Shared Technology	"The degree partners value the technology contributed by the relationship leading to a stronger relationship if both parties benefit" (Powers and Reagan 2007; Wilson 1995)	Martin et al. 1991; Ogilvie et al. 2018

Sales Technology (General)* - Hunter 2019; Hunter and Perreault 2006; Hunter and Perreault 2007; Ingram et al. 2002; Onyemah et al. 2010; Rayburn et al. 2021; Robinson et al. 2005; Román and Rodríguez 2015; Ryding 2010; Schillewaert et al. 2005; Schrock et al. 2016; Sharma and Sheth 2010; Singh et al. 2019; Sleep et. al 2020; Tanner Jr. and Shipp 2005; Tanner Jr. et al. 2008 *note:* *= Unclear of the precise sales technology the researcher is referring to.

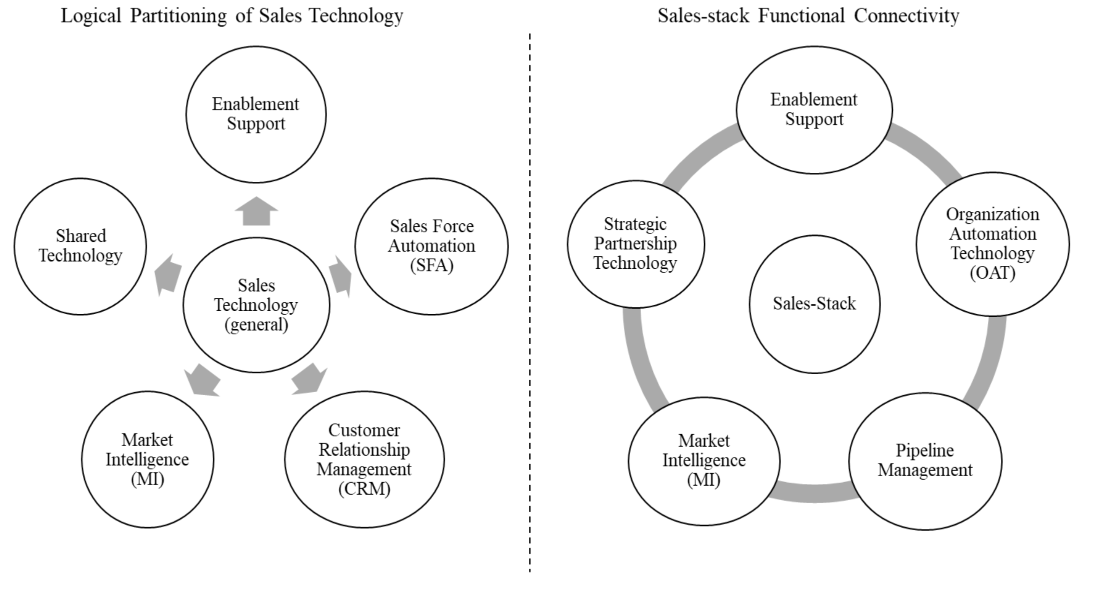
Logical Partitioning of Sales Technology

Academic literature has made strides in sales technology research to compliment the growing implementation in corporate settings. However, current literature is logically partitioned into technology classifications. Logical partitioning or deductive classifications is where research imposes a classification on the data (Hunt 2002; p.201). While this a priori classification is a valid method for creating a classificational schema (Harvey 1969 p.334), there is concern using this method.

The first criticism is that logical partitioning results in monothetic classification (Sneath & Sokal 1973). In monothetic classifications, all members of a category possess all attributes in that category. As alluded to above, sales technology doesn't flow linearly from one system to the next, but sales technology flows fluidly into multiple systems (sales-stack) to support the sales team (*see figure one)*. For example, market-intelligence technology can be used to collect category insights but then flow into an automation system. In a logically partitioned classification category insights could only be an attribute of one category not both.

The next criticism when using logical partitioning is that it, assumes the researcher has a refined understanding of the classified phenomena (Harvey 1969, p. 366). That is the researcher is an expert in the field and the characteristics that are using to classify each technology. Without solidified characteristics of each sales technology there can be an infinite number of classifications causing confusion within literature streams. Furthermore, with the growing number of entrants and mergers of ST a much more sophisticated classification is needed.

Figure 1. Sales technology vs. sales-stack attribute differentiation



Note: Connectivity of multiple sales technologies is the pivotal characteristic that transitions sales technology into a sales-stack

Grouping Procedures

An alternative to logical partitioning is grouping procedures. As opposed to logical partitioning; grouping procedures follow inductive reasoning. That is, results are pulled from data to better understand the categories that make up the classification (Hunt 2002). The first difference between logical partitioning and grouping procedures is that in grouping procedures all groups share common characteristics. Since the goal is to break apart sales technology to better understand the optimum composition for a sales team, it would be expected that each technology shares common characteristics. Polythetic classes allows for each class to share numerous characteristics but not all of them (Sneath and Sokal 1973).

The second difference between logical partitioning and grouping procedures is that there are no empty classes in grouping procedures. With logical partitioning empty classes are acceptable to have because it allows for areas of future research to be explored and expand the field. With group partitioning since all classes are pulled from data (inductive) no empty classes exist.

Frank and Green (1968) suggest that grouping procedures be considered “preclassification techniques” since these techniques describe natural groupings that may lead to a conceptual framework for classification.

Criteria for Classificational Schemata

Scholars continually expand on the growing need to research ST with increased specificity in conceptualizing sales technology (Hunter 2019). Without solidified classes of sales technology, the literature stream maintains a sense of ambiguity in understanding how ST can impact a salesforce. The fast pace digitization of ST causes borders of prior literature to become murky due to emerging tools and increased functionality of past tools.

Introducing characteristics that can carve out the foundation for organizing phenomena is representative of the first step in theory development (Hunt 1983). Extrapolating ST characteristics into a systematical hierarchal classification can help diffuse the continual blending of emerging technologies.

The following sections draw on Hunt’s (2002) criteria for evaluating classification schemata:

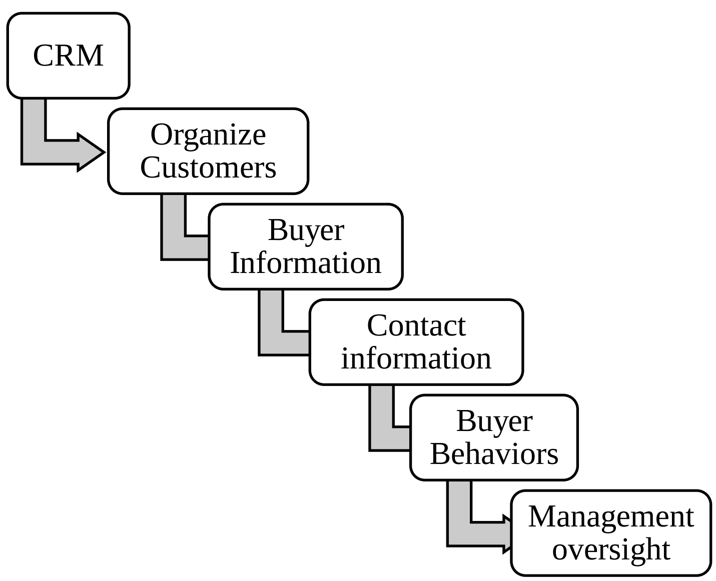
1. Does the schema adequately specify the phenomenon to be classified?
2. Does the Schema adequately specify the properties or characteristics that will be doing the classifying?
3. Does the schema have categories that are mutually exclusive?
4. Does the Schema have categories that collectively exhaustive?

Phenomenon Being Classified

The phenomena being classified is *sales technology (ST)* based off of the characteristics of the functional purpose it provides to the sales organization. Using Hunter and Perreault's (2007) definition, ST is defined as "Information technologies that can facilitate or enable the performance of sales tasks." While most sales researchers understand that a customer relationship management system (CRM) aids a salesforce in organizing their customers. Few, researchers deep dive into the characteristics that make up the CRM system and the benefit of the technology to the salesforce.

Breaking down the technologies into their functional characteristics allows for researchers and mangers to understand the common characteristics of the technology to better layer it into streamlined sales-stacks. In other words, once you break down the components of the technology, you can synergize the commonalities together to create a super charged version in the form of artificial intelligence and machine learning (Syam and Sharma 2018). Figure two provides an example of how a functional characteristic breakdown can look.

Figure 2. Characteristic break down of CRM System



Towards a Positive Theory

Researchers agree that ST supports the salesforce allowing them to be more efficient and effective (Hunter 2019). However, two camps exist when looking at ST research. 1) Researchers blanket ST as one tool that supports the salesforce. While inherently correct, support does not capture the type of technology that is being exploited. That is, CRM tools do not provide the same function as does a digital library. 2) Researchers look solely at a single tool to make the claim that the ST aids the salesforce. For example, research looks solely at CRM systems or just market intelligence's impact on the salesforce. Once again, the results are intuitively correct under the premise that specific ST tools impact the salesforce. However, without dissecting the malleable support tools that feed into the specific system, researchers are not accounting for variance in their studies.

Although most research in the sales technology area, in either camp, presents empirically testable results, researchers' ability to develop meaningful positive theory is limited by not providing strict validation of the constructs being tested. By breaking apart each ST and piecing the aggregate together (sales-stacks), future research can better develop positive theory with a focus on developing pragmatically meaningful normative theory.

Building Blocks of Sales Technology

A major grievance with logical partitioning is that it, "presupposes a fairly sophisticated understanding of the phenomena being investigated, [or] else the classification involved may be totally unrealistic, nothing better than an inspired guess" (Harvey (1969, p. 366). In order to combat allegations of creating inaccurate assumptions of sales technology, unstructured interviews were attained with 10 sales professionals to understand how sales technology support their daily sales efforts. Phenomenological insights allow researchers to better understand the building blocks of technology as practitioners have a much closer involvement of emerging tools.

Criteria of Interviews

Salespeople are considered boundary spanners, because they are the face of the company in the customers eyes. Salespeople still perform many support roles within the sales organization. Many of these roles are responsible for maintaining the ST that the salesforce utilizes. In order to better understand in the entirety of how ST is used throughout the sales organization the sole screening criteria for the interviewees was that they are under sales organization in their firm. Participants were chosen from 9 different industry sectors with a broad array of sales experience, and varying length of tenure at their organization *see table 2*.

Table 2. Backgrounds of Salesperson Interviews

Industry	Employment Title	Direct Reports	Organization employees	Tenure at organization	Sales Experience
Biotechnology, Medical	Sales Executive	2	50	2 Years	6
Home and Office Products	VP eCommerce and Digital Marketing	6	16,500	1 Year	24 Years
Technology	Director of Customer Success	2	50	3 Years	6 Years
Manufacturing	VP of Channel Success	1	151	2 Years	8 Years
Containers and packaging	Business Development and Competitive Intelligence Sales Manager	0	4500.00	6 Months	15 Years
Food and Beverage	Education Region Account Manager	1	263,000	7.5 Years	7.5 Years
Consumer Staple	Director of Retail Sales	3	106	1.5 Years	17.5 Years
Home and Office Products	Sr. Key Account Manager	1	3,000	4.5 Years	4 Years
Healthcare	HIV Prevention Specialist	0	11000.00	1 Year	6 Years
Communication Services	Video Account Manager	0	103,549	4 Years	4 Years

Interview Methodology

The goal of the interviews was to understand how a salesforce uses the technology that is available to them to complete their role. The participants were a bit skeptical about sharing how their internal systems work, because they consider their internal process a strategic advantage and some of their technology proprietary. To ensure that the participants would be as candid as possible, anonymity of both their name and organization was guaranteed. The interviews followed the same format, each participant was asked to list all ST they use in their sales role. Once they had listed out all pieces of ST they could think of, they were asked to explain what each piece of technology does as if they were explaining it to someone who has never been in a corporate setting before.

Where the technology starts

Forcing, participants to oversimply the explanation of what they use the technology for enables researchers to understand the workflow of how data moved [or didn't move] from system to system as well as get a much granular understanding of the function each piece of ST provides. A normal exchange tends to follow a similar pattern:

Participant: *"We use SAP to pull our sales data"*

Interviewer: *"Who's sales data? Category or your companies?*

Participant: *"Our own numbers, we use Nielson to get category data"*

Interviewer: *"So what numbers does SAP pull?*

Participant: *"Current sales, GM, Team/ organization sales numbers"*

Interviewer: *"Can you see how you're rolling up toward your quota in SAP"*

Participant: *"No, we get an Excel flash report in the morning to see that"*

Interviewer: *"Where does the flash report get their numbers from?"*

Where the technology goes

Each interview followed the same format of answer and interjection until the participant could no longer trace the technology back to where the original data was coming from or the interviewer could logically understand how the data was being acquired. At this point the interview moved to what happens with the data the salesperson possess. Similarly, an example of this exchange:

Interviewer: *"…So you have your sales data from SAP. What do you do with it?"*

Participant: *"I use it to update my customers on how the year is going"*

Interviewer: *"How do you present the numbers"*

Participant: *"I have a monthly meeting with them"*

Interviewer: *"Is there something you use to show them or do you just write the number on notebook paper and hold it up?"*

Participant: *"Oh, I use PowerPoint!"*

Interviewer: *"Do you have a company template or do you design our own"*

Participant: *"No I make my own. Technically I designed it once and update the numbers each time"*

Overall perspective of interviews

Although this sounds like a very tedious process, after the first few exchanges participants understood the level of detail needed to get to the starting [or ending] point of the ST and the interview process sped up. Each interview took an average 60 minutes to complete. By the end of each interview the participant was usually in astonishment of how many systems they use to do their everyday tasks. Upon completing all interviews, it was eye opening the enormous spectrum of support or lack of support sales technology provides to each salesperson. In some cases, an organization had one system that automatically updated with everything they needed to do their job and the interview was spent explaining every function this wholistic piece of ST provided. On the other side of the spectrum, the entire interview was spent explaining how every time the participant has a meeting, they have to go to six different systems and talk to four different people to build their presentation. Extrapolating the themes that each interview presents allows for researchers to bucket common themes creating an interpretation of common technologies used across organizations and industries alike.

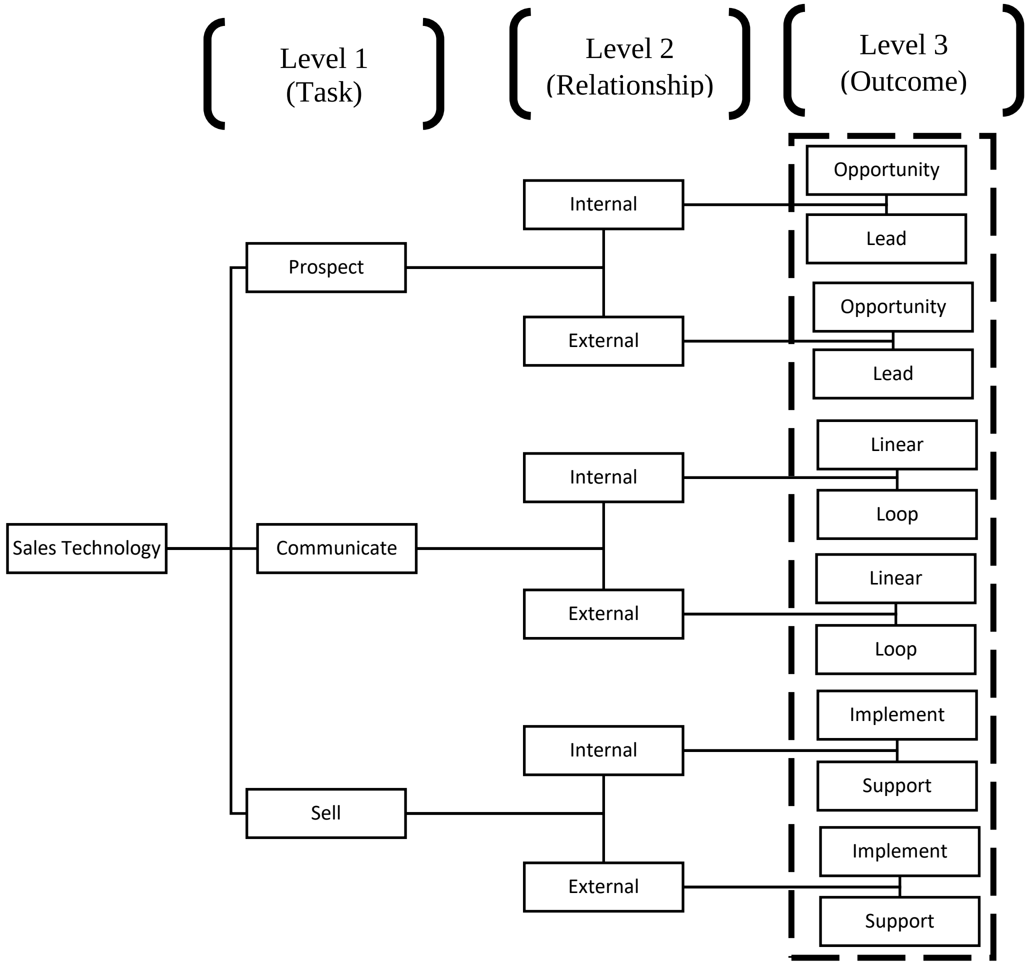
Properties of the classification

Contrary to the large differences between the resources each salesperson has available to them, many similarities expose themselves when drilling down to the actual function the technology provides. Critically sorting the similarities and differences of each technology allows three hierarchical dimensions to reveal themselves:

- The task the salesperson is working on:
  - Prospect,
  - Communicate,
  - Sell
- The dyadic relationship the salesperson is working within:
  - Salesperson – Organization (Internal),
  - Salesperson – Customer (External)
- The specific desired functional outcome

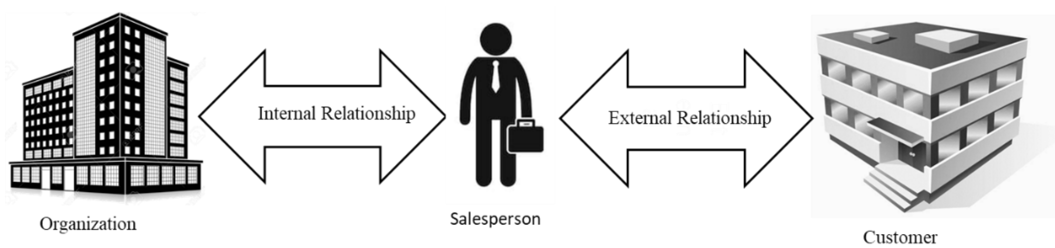
Figure three summarizes the proposed classification schema. The first level of the hierarchical classification differentiates among the functional task's salespersons are trying to achieve. The second level of the hierarchal classification differentiates between the dyadic role the salesperson is practicing within *see figure four.* The third and final level of the hierarchical classification differentiates between the desired outcome the sales technology provides.

Figure 3. Sales Technology Classification Schemata



NOTE: dotted line represents the aggregate of all single purpose technologies working together (sales-stack)

Figure 4. Salesperson Boundary Spanner Relationship



NOTE: Salespeople are known as boundary spanners based on the internal relationship with their organization and external organization with their customers

Prospecting

Prospecting is a fundamental step of the personal selling process (Jolson and Wotruba 1992). A salesperson can't begin to do their job of actually selling a product until they are able to find a reputable buyer. At this stage of the selling process salesforces can easily get bogged down with time consuming hunts in pursuit of buyers.

Internal versus external prospecting

As organizations grow, internal databases are created of potential prospects that can turn into a future buyer. A previously unclosed customer can eventually turn into a potential buyer as an organization grows its product selection or adapts to a changing market. Maintaining an organized internal database of buyers allows for a salesforce to spend less time searching for buyers and more time implementing and closing sales.

In order to keep a business growing, it is imperative for a salesforce to continually keep expanding its customer base. One of the most time-consuming functions for a salesforce is to externally prospect for new customers. Technology has allowed for a salesforce to cut down on time spent looking for prospects by creating filtered searches, and premium accounts (i.e., LinkedIn sales navigator). However, even with tools to find a prospective customer, salespeople still need to search for contact information to move on to a communication phase of the selling process.

Opportunity versus lead

The main difference between an opportunity and a lead is the ability to qualify the buyer. That is every prospective buyer starts out as a lead until the salesperson qualifies that they could be a potential opportunity. Qualifying the buyer consists of making sure the product the seller has, satisfies the buyer's needs. Sales technology differentiates internal opportunities and internal leads by if they have enough information to qualify buyer. An example from the interviews is in the medical sales industry. A new pharmaceutical drug was rolled out. The salesforce knew the doctors in their territory that treated patients with symptoms the new drug. The doctors would be considered *opportunities* because they are already qualified buyers (prescribers to use correct medical sales jargon). Furthermore, this particular sales organization also has a database of all medical practices in each territory. Any physician that has not done business with this organization is considered a *lead* because the salesperson is unsure of the cliental that they treat on a day-to-day basis.

External leads and opportunities follow the same criteria within the schema. External opportunity technology allows for a salesforce to qualify leads or streamline the conversion from lead to opportunity during their search. The external opportunity process can increase efficiency in the prospecting stage. However, there will always be external leads that are found that can't be converted until a salesperson moves through the discovery phase with the buyer.

Communicating

Research demonstrates that the ability to communicate effectively is critical to performance (Wester 1968; Boorom, Goolsby and Ramsey 1998). Although communication is not considered a formal step in the selling process, effective communication is a vital component that compliments all stages of the sales process.

Linear versus loop

Salesforces use many different mediums to transmit their messages, whether it be traditional email, email blasts, websites and newer technology like social media platforms. Communication can be used to convey a variety of messages. However, the main difference between linear and looped communication is the feedback that the salesperson receives. In a linear setting the salesperson is sending out a blast to a large number of receivers while expecting no response in return. In a looped feedback scenario, the salesperson is using technology to create a connection with their counterpart. A connection could originate via social media to interact with customers, or by sending internal emails to understand how their ad allowances can be used to close a sale.

12 Themes of Sales Technologies

Internal Prospecting Opportunity Tools

Prospecting is the first step in the sales process. To ensure there is continual business within the organization it is a necessity to maintain relationships with qualified buyers. Having an organized database of qualified opportunities reduces the time a salesperson spends tracking down contacts, allowing them to spend more time on closing deals. Examples of technologies that fall into this area are *Airtable*, which allows organizations to upload spreadsheets turning them into a database; and *Contractually*, which allows salespeople to identify and stay connected with connections in their network.

External Prospecting Opportunity Tools

The difference between Internal and external opportunity tools is within the context salespeople are working. Referring to Figure 4 salespeople are either working with their own organization or working with the supplier (customer in the diagram). When working with suppliers the salesperson is not necessarily in direct contact with the supplier, however, they are using external tools to help qualify leads. Examples of this could be Spokeo, which helps track down contacts of buyers or external databases that allow a salesperson evaluate the company to understand their buying needs.

Internal Prospecting Lead Tools

As alluded to above the main difference between a lead and an opportunity is whether the prospect has been qualified. When a supplier has not been qualified it stays within the lead category. Lead prospecting tools are used internally to assess missed or untapped opportunities. Internal lead tools allow for salespeople foresee trends that are becoming available. By analyzing and projecting sales trends of current products salespeople or AI technology can extrapolate projections of characteristics salespeople should look for when prospecting for new customers.

External Prospecting Lead Tools

External lead prospecting technologies are the proprietary eponym of organizations. That is the technology used to aid salespeople in prospecting is always perceived to be externally focused. However, without the basic internal understanding of the necessity for the product, external lead prospecting technologies tend to lead salespeople on an allusive witch hunt rather than a strategic search for prospects.

The most familiar form of technology in this area is *LinkedIn Sales Navigator*. These are tools that allow a salesperson to find potential buyers throughout the world. Furthermore, these technologies expand the reach of a salesperson to untapped markets. Most tools have the ability to prefilter prospects, saving the salesperson time in their lead generation process.

Internal Linear Communication Tools

Communication is a vital part of any sales transaction. Reducing the ambiguity between an organization and their customer can be the pivotal factor that converts opportunities to sales. While most consider communication to be a back-and-forth process, research in integrated marketing communication looks at it on a spectrum (Finne and Gronroos 2009). On one side of the spectrum there is no integration, or one-dimensional communication. That is, a message is formulated, sent and received. The opposite side of the spectrum is relationship communication where multi-dimensional factors are taken into consideration and a feedback loop occurs.

Internal linear communication technologies are one-dimensional communication technologies that are sent out within an organization where no feedback is required. Salespeople receiving daily quota flash reports, NPD teams sending out technical specifications of a new product, and memos from board of director meetings are all common linear communications examples mentioned during the interviews.

Internal Loop Communication Tools

Internal loop communication tools are multi-dimensional technologies that require feedback from the salesperson. Sales technologies in this area include internal communication tools like Google Hangout, which allows virtual conferencing that can help remote team members connect with one another or in pipeline management where a salesperson can communicate with NPD teams during the creation of new products. In all cases, the communication is occurring intra-organizationally and is not seen by the customer.

External Linear Communication Tools

Switching from the salesperson-organization dyad to the salesperson-customer dyad external linear communication technologies allow for salespersons to continually communicate information to their customers. Technologies can be websites that help inform customers about offerings, email blasts about timeline of new product launches, and/or means of advertising to promote products. In all cases these technologies are one-dimensional and pushes the information out inter-organizationally.

External Loop Communication Tools

External loop communication technology allows for salespersons to interact with their target market. Salespersons are no longer blasting communication to their customers but they are opening a dialect in hope to receive feedback. The most popular form of this type of technology is social media. On social platforms organization have the ability mass communicate to their target market as well as respond to inquiries allowing them to streamline the selling process. Other areas that this technology can be used in customer support or even API (application programming interface) where the salesperson isn’t directing handling the communication but instead the organization and customers systems are communicating with each other. All inter-organizational communication with a feedback loop would fall into this category.

Internal Implementation Selling Tools

Implementation tools allow a salesperson to close a sale. These are necessary systems a salesperson utilizes to get the *ink to paper*. Internally the salesperson needs to finalize the pricing based on company policy, place orders into the system to ensure on time delivery. These technologies are usually the last system that a salesperson touches within the selling process. Examples of these are DocuSign, AS400 (inventory allocation software), or anything that is organization specific to make sure the sale goes into the correct accounts and inventory is correctly allocated.

Internal Support Selling Tools

Internal support tools are the technologies that support a salesperson in their implementation of the sale. These are technologies the customer doesn't necessarily see but play a fundamental role in aiding the salesperson. Some examples that were mentioned among the administered interviews were digital libraries, demand planning tools, and product information management (PIM) systems.

External Implementation Selling Tools

As customers begin to grow their own technological presence, they have developed interfaces that salespeople interact with instead of face-to-face sales pitches. Built with complex artificial intelligence, these systems replace the buyer's role, forcing salespeople to interact with the system. Some examples are Amazon's Vendor Central, or Walmart's supplier center. In all cases implementation selling tools are used to directly close the sale.

External Support Selling Tools

Organizations continually upgrade their technology infrastructure to streamline the selling process. External support selling tools allow salespeople to work more efficiently to meet the growing demand of quicker turnaround times. These types of technologies act as intermediaries between the organization and the customer to aid in the selling process. A frequently mentioned ST is Salsify. Salsify allows for organizations to load products into their interface. Salsify then has an API[1] link to retailers so organizations can directly send product setup information to their customers.

Creation of a Sales-stacks

The 12 themes exhaust the possible functional use of sales technology. It is naïve to think that every salesperson has a piece of technology that fits in each category. ST is put in place to better aid the salesperson in doing their job, but not necessarily do their job for them. Furthermore, many pieces of technology can fulfill multiple roles in a salespersons process. Organizations are not looking for a technology that supports the salesperson in every aspect of their selling process but where the organization can see the largest ROI when implementing ST into a sales team.

A sales-stack does just that. Instead of a single piece of ST to help the salesperson with a single aspect of their selling process. Sales-stacks are an aggregate of the 12 technological functions that each piece of technology would support. Stacking allows for organizations to pick and choose what they perceive as the best ST to receive largest ROI. Smaller organizations can purchase a ST stack that fits their budget. Sales-stacks may sometimes be purchased through a single branded tech firm, but often sales stacks are arranged using tools acquired from a variety of suppliers, all with the common goal of streamlining the selling process and thereby increasing sales effectiveness.

[1] API (Application Programming Interface) is a software intermediary that allows two applications to talk to each other

II. INDIGENOUS THEORY OF SALES-STACKS

With concerns over the lack of new marketing theory development, Hunt (2020) lays out a seven-step approach for the development of indigenous theory that aims to harmoniously tie growing research streams into parsimonious wholistic theory. This seven-step method, while not empirically testable, provides the foundation for creating valuable theoretical and conceptual frameworks critical to developing new theory (Hunt 2020). The current research chapter addresses the first four steps in the indigenous theory development process with the remaining three steps positioned for future research.

Step 1: Problem Identification

Academic literature has made strides in sales technology research to compliment the growing implementation in corporate settings. However, current literature is logically partitioned into technology classifications. Logical partitioning, or deductive classification, imposes a classification structure on the data (Hunt 2002). While this a priori classification is a valid method for creating a classificational schema (Harvey 1969), there is concern with using this method.

The first criticism is that logical partitioning results in monothetic classification (Sneath and Sokal 1973). In monothetic classifications, all members of a category possess all attributes in that category. As alluded to above, sales technology doesn't flow linearly from one system to the next, but flows fluidly into multiple systems to support the sales team. For example, market-intelligence technology can be used to collect category insights which then flow into an automation system. In a logically partitioned classification category insights could only be an attribute of one category not both.

The next criticism when using logical partitioning is that it assumes the researcher has a refined understanding of the classified phenomena (Harvey 1969). That is, the researcher is an expert in the field and about the characteristics of each technology that is being classified. Without solidified characteristics of each sales technology there can be an infinite number of classifications created causing confusion within a literature stream. Furthermore, with the growing number of entrants and mergers of ST a much more sophisticated classification is needed. Thus, we propose and define the term sales-stacks as the aggregate sales technologies that provide a powerful, connected, easy-to-use experience for every sales role.

Step 2: Evaluation of Current Theories and Frameworks

A necessary step within the indigenous theory development is to evaluate extant theories prior to the develop of a new theory or a theory of theories. From the literature synthesis, twenty-two unique theories were used to ground sales technology research. Table 4 provides an overview.

The majority of these theories focus on a single technology adoption but lack the complexity to address the problem sales-stacks solve -- how to leverage all selling and sales management technology into success for the firm and firm stakeholders. To add more clarity the top twenty-seven percent of theories used in sales technology literature are evaluated to see if they can be adapted to explain sales-stacks (see Table 5). While some have a foundation that seem to ground sales-stacks, none account for the interconnectivity of all sale technologies.

Table 3. Identified Theories in Theory Synthesis

Theory Used	Frequency
Technology Acceptance Model* (TAM, TAM2)	15
Diffusion of Innovation Theory (DOI)	5
Social Exchange Theory	4
Task-Technology Fit Theory (TTF)	4
Commitment-Trust Theory	3
Job-Demands Resource Theory (JD-R)	3
Social Cognitive Theory (SCT)	3
Expectancy Theory	2
Technology-to-Performance model (TPC)	2
Adaptive Structuration Theory (AST)	1
Agency Theory	1
AIDA Model	1
Balance Theory	1
Boundary Role Theory	1
Ecosystem Theory	1
General theory of marketing ethics	1
Organizational Support Theory (OST)	1
Social Influence Theory	1
Social Learning Theory	1
Technology-Mediated Learning Theory	1
Theory of Planned Behavior	1
Unified Technology Acceptance and Utilization Theory (UTAUT)	1

note: Numerous articles were grounded by multiple theories. n= 32 of the reviewed articles (44 articles were reviewed, 11 articles did not mention a theory, 1 article reviewed ST adoption theories and was excluded from count) * = the combination of TAM and TAM2

Table 4. Extant Theories in Relation to Sales-stacks

Theory	Description	Strength	Weaknesses	Relationship to Sale-stack
Technology Acceptance Model (TAM)	Examines how users come to accept and use a technology	Explains how salespeople use technology in the workplace	Only focuses on a single piece of technology not on the interconnectivity of multiple technologies	Minimal
Diffusion of Innovation Theory (DOI)	Examines how, why, and at what rate new ideas and a technology spread	Explains how salespeople adopt technology into their workflow	Only focuses on a single piece of technology not on the interconnectivity of multiple technologies	Minimal
Social Exchange Theory	Studies the social behavior in the interaction of two parties that implement a cost-benefit analysis to determine risk and benefits	Explains the cost-benefit of a salesperson adopting new sales technology	Does not facilitate the adoption of cost-benefit within the technologies	Minimal
Task-Technology Fit Theory (TTF)	Examines the degree to which a technology assists an individual in performing their task	Explains sales technology adoption and adaption for changing environment	Only focuses on a single piece of technology not on the interconnectivity of multiple technologies	Moderate
Commitment-Trust Theory	Studies the fundamental factors, of trust and commitment, that must exist for a relationship to be successful	Focuses on the trust the salesperson instills in the technology to achieve their goal	Does not facilitate the trust of the interconnectivity between sales technologies	Minimal
Job-Demands Resource Theory (JD-R)	Occupational stress model that suggests strain is a response to imbalance between demands on the individual and the resources he or she has to deal with those demands	Focuses on the need to improve and update organizational sales technology to ensure the balance between job and resource's	Only focuses on a single piece of technology not on the interconnectivity of multiple technologies	Minimal

Step 3: Identifiable Characteristics of New Theory

The main property that distinguishes separate sales technologies from sales-stacks is the connective nature of the technologies. As organizations invest and improve their technological fortitude the internal systems become inter-connected allowing for technologies to communicate and streamline sales processes (*see figure 1)*[2]. Sales-stacks act as the catalyst that can move raw inputs into workable data and synergize that data into increased salesperson performance.

Marketing has seen an uptick in calls for more indigenous theories to explain evolving areas and address fundamental marketing problems (Hunt 2020). Currently, no literature has expanded into the intra-connectivity of sales technology. A key cornerstone of indigenous theory development is the formulation of foundational premises (FP) that acts as the bedrock for future theory development. Thus, the proposed six foundational premises of sales-stacks that stem aim to address the fundamental problem of how the intra-connectivity of sales technologies should be affected to enhance sales-organization performance. Table 5 presents a synopsis of the FPs described below.

Step 4: Development of Foundational Premises

As noted above the key attribute that differentiates sales technology from sales-stacks is the connective nature of all the sales technology harmoniously interconnecting into a robust platform (stack) that allows for salespeople to be more efficient and effective. Thus, the grounding premise that allows for sales-stacks to be differentiated and further researched is stated as:

FP1. **Sales technologies connectivity to one another is the fundamental property that distinguishes sales technology from a sales-stack.**

[2] Figure 1. can be found in previous chapter one

When the stack of sales technologies veers too far away from seamless interconnectivity (sales-stacks), organizations have a *franken-stack.* A term adopted by users, in frustration of the collection of disparate tools that require work arounds to be usable. Franken-stacks not only hinder the sales technology within an organization but hinder salesperson performance, efficiency and effectiveness. Research suggests a majority of sales technology introductions fail to increase salesforce performance in part because of complexities and frustration over implementation (Alavi and Habel 2021; McKinsey and Company 2017).

Addressing concerns of franken-stacks, foundational premise two addresses that the composition of sales technologies that make up a sales-stack should be idiosyncratic and compatible – making them user friendly, which may aid in adoption (Alavi and Habel 2021). Further, one reason for SFA adoption involves the issue of the technology stack not providing sufficient benefits relative to the cost of learning how to use the tools (Zoltners et al. 2021). For example, technologies are duplicated in the sales-stack cause salespeople to interact with multiple systems for the same purpose. Additionally, new technologies being added to the stack should be compatible in the sense that they can easily be implemented to connect with one another. This ensures a streamlined implementation process and ensures that the new technology integrates with the incumbent composition of the stack.

FP2: **Idiosyncratic and compatible sale technologies are the building blocks of an effective sales-stack.**

Once the sales-stack is connected they are adopted by the salesforce and disseminated through the organization. Just like sales technologies, sales-stacks are implemented to help the salesforce be more efficient and effective at their position. However, for sales-stacks to be optimal for efficiently and effective information, the internal organization needs to provide inputs. While the end user of the sales-stack is the salesforce, it is a necessity for other organizational teams to be well connected to the sales-stack to ensure streamlined communication throughout the organization.

FP3. **Sales-stacks are adopted by the salesforce and disseminated through the organization.**

There is a need for management advocacy for these technologies throughout all organizational positions that will interface with the digital transformation of the sales organization (Zoltners et. al., 2021). The end value of a sales-stack is the ability to support the sales team, however, the overall value creation of the sales-stack is with intra-organizational and inter-industry adoption. In other words, if the rest of the organization is not using it, or it doesn't have an application in the industry the organization works in, the stack loses its purpose and begins to have traits of a franken-stack.

FP4. **Value of sale-stacks is created by intra-organizational and inter-industry adoption.**

The goal of any sales-stack is to alleviate stressors put on the salesforce by implementing technology (sales-stack). With industrial environments exponentially changing new technology is constantly being introduced. Sales-stacks flatten the technology adoption curve of a salesforce. Since all the sales technologies that make up a sales-stack are interconnected, salesforces have some familiarity when integrating new technology (Alavi and Habel 2021). This may come in the form of similar user experience (UX), workflow management, or program language. In any case, learning the new technology is simplified because of familiarity with the incumbent sales-stack.

FP5. **Sales-stacks flatten the technology adoption curve of a salesforce.**

Lastly, continual adoption of progressive technological tools is needed to maintain an effective sales-stack. As the sales environment continues to change, so does the sales-stack’s technology. Failure to maintain cutting edge technology pushes a sales-stack into retrograde causing it to move towards a franken-stack. Sales-stacks need to be consistently evaluated and updated to achieve optimal performance. Consequently, salespeople must constantly adopt to new user experiences.

FP6. **Continual adoption of progressive technological tools is needed to maintain an effective sales-stack.**

Table 5. Six Foundational Premises of Sales-stacks

Foundational Premise		Logic
FP1.	Sales technologies connectivity to one another is the fundamental property that distinguishes sales technology from a sales-stack	When ST's flow from one system to another (i.e., MI-> CRM) there are now two STs that need to be considered when assessing causality. Sales-stacks accounts for the flow between the STs.
FP2.	Idiosyncratic and compatible sale technologies are the building blocks of an effective sales-stack	Sales-stacks need to encompass the adequate ST for a salesperson to complete their task. Additionally, ST need the compatibility to integrate with one another to insure the efficiency
FP3.	Sales-stacks are adopted by the salesforce and disseminated through the organization	Sales-stacks originate within a sales organization to improve efficiency and effectiveness. Then they are pushed through the organization to get the malleable data needed to maintain the efficiency and effectiveness
FP4.	Value of sale-stacks is created by intra-organizational and inter-industry adoption	Sales-stacks earn their value from increasing a salesforces efficiency and effectiveness. If the organization and/or industry does not utilize the sales-stack, it becomes an obsolete piece of technology.
FP5.	Sales-stacks flatten the technology adoption curve of a salesforce	Based on the compatibility characteristics of FP2, new technology introduced to a salesforce should be similar to the technology they currently use. Thus, reducing the salesforce’s apprehension/ learning curve.
FP6.	Continual adoption of progressive technological tools is needed to maintain an effective sales-stack	Sales-stacks need to have the resources and capabilities to keep up with the sale environment. (i.e., As the sales environment changes, so does the sales-stack)

Continual Research

The delineation above shows that ST plays a dominant role within the selling organization. The hope is that the typology and subsequent foundational premises act as a launching point to guide future research towards a solidified understanding of how sales technology and sales-stacks play a fundamental role in the selling process. In part with Hunt's (2020) process for indigenous theory, identified below are key areas that the remainder of this research will ensue to test the proposed sales-stack theory.

Operationalizing Sales-stacks

First and foremost, research needs to focus on how to measure organizations' sales-stacks. Sales-stacks differ from organization to organization and can be considered their strategic advantage. Building on dynamic capabilities theory, technological capabilities are more effective in competitively stable environments because firms are more likely to automate processes during these times (Wilden and Gudergan 2015). As the digital landscape becomes more diluted with new entrants, the overall landscape shows no signs of stabilizing. Additional research should measure how well an organizations sales-stack performs its functions or internal technological capabilities based on functionality to better understand the key factors that allow a company to utilize technology within a precarious environment.

Malleable Inputs

Sales-stacks cannot run to their full potential without the proper inputs to make them effective. Similar to how the internet doesn't work well if you don't have a laptop or cell phone to log on. Malleable inputs are the shell that makes up a sales-stack to be utilized. Without the proper inputs the sales-stack is considered obsolete. Artificial intelligence predictions are only as good as the market intelligence data that it is based off. A more precise understanding of the how malleable inputs impact sales-stack capability can support progress of empirically testable sales-stack research.

Usage Barriers

Malleable inputs are the bare minimum of what an organization needs to make sales decisions. Implementing sales-stacks or components of sales-stacks can be chaotic well trying to still maintain normal business processes. Further research should look at the moderating roles of adoption barriers that can hinder or help the implementation of a sales-stack and sales-stack technology.

Just because a sales-stack is put into place, doesn’t mean that the systems are being utilized. How salespeople come to take the technologies for granted or why salespeople opt not to use technologies deserves attention. Intuitively, ST should aid the sales process however, moderating usage barriers deserves attention to better understand the impact unused technologies have within an organization

Artificial Intelligence

ST research typically looks at sales outcomes like efficiency and effectiveness (Hunter 2019). However, organizations that have digitally advanced systems give themselves greater opportunities to beta test future technologies. As AI systems grow to the point where buyer and sellers’ internal systems are talking to each other, organizations are looking for strategic partners to test processes. Organizations who have complimentary strategic partners need to better understand the non-tangible outcomes of digitally transforming internal systems. The feedback loop from outcomes to sales-stacks is an ever-prevalent need within the literature stream.

III. MEASURING PERCEPTIONS OF SALES-STACK EFFECTIVENESS

Introduction

Firms have turned to sales technology to increase their workforce efficiency and effectiveness (Hunter and Perreault 2007). Sales technology substitutes human capital for automated systems (Jones, Sundaram and Chin 2002; Speier and Venkatesh 2002), mitigates buyer-seller interactions in place of self-service approaches (Fleming and Artis 2010) and is leveraged as a recruitment and job satisfaction tool (Limbu, Jayachandran and Babin 2014). Just as salespeople act as boundary spanners between their organization and customers, sales technology is leveraged as a catalyst between an organization's resources and the salesperson's desired goal. However, decision makers who prematurely elect to implement new sales technology under the premise that it will transcend the salesforce to a new level can unintentionally hinder the processes of, not only, the salesforce but the organization as a whole (Buehrer, Senecal and Pullins 2005).

Numerous studies have found that the investment into new sales technology does not always prove beneficial to the salesforce and partnering business functions within the firm (i.e., finance, marketing, business development etc.). Lack of predefined, objective goals prior to the implementation of sales technology can hinder the acquisition and use of such technology (Rivers and Dart 1999). Attaining sales technology under the premise of feeling *left behind* by competitors also has not been found to influence sales technology adoption (Jelinek, Ahearne, Mathieu and Schillewaert 2006). Jelinek et al. (2006) infer that it could be salesforces who are implementing new technology are naive about the technologies their competitors' harness. A parallel disposition is that salesforces are biased in that if they don't harness technology neither does their competitors (Klompmaker 1981).

Sales technology acceptance has been looked at from many perspectives predominantly from internal versus external barriers (Buehrer, Senecal and Pullins, 2005; Parthasarthy and Sohi, 1997). Once the decision to implement the technology is agreed upon, barriers must be overcome to grasp the full effect of the technology. Internal barriers focus on salesperson characteristics like the necessity for training, based on competence, reluctancy of use and perceived benefit. While external barriers look at the organizational capabilities like the infrastructure of the organization and compatibility with outside clients. Salespeople's usage tolerance to sales technology is curvilinear in the sense that the increased usage of sales technology will positively impact performance until the inflection point, but over usage can hinder performance (Ahearne, Srinivasan and Weinstein 2004).

Intuitively sales technology is implemented to aid the salesforce in their everyday responsibilities. Thus, over usage of systems should be alleviated under the premise that salesforces should be focused on relationship selling with their customer and not harassed with technological formalities. Sales technology manufacturers understand the strain of juggling multiple technological systems that don't cohesively integrate with each other. In order to better facilitate salesforce demands of a universal system capable of handling all necessary capabilities; technology manufactures have acquired and merged with competitors to harness core competencies. A simple illustration of such inertia in practice arises when practitioners commonly expressed that if an organization uses Microsoft outlook for email, they tend to use Microsoft teams for video conferencing, and PowerPoint for presentations. Similarly, if an organization uses Google Gmail for an email platform, they lean towards using Google Hangout for video conferencing and Slides for presentations.

Adversely, not all sales technologies needed to support the salesforce are offered by a sole manufacture or supplier. Thus, sales technologies have been made to integrate with parallel technologies. Organizations have begun piecemealing sales technologies needed to support their sales force into one cohesive sales-stack (Bartolacci 2019). Identifying the types of technologies needed to support the sales team can be achieved by identifying bottle necks in the selling process. However, organizations must be weary of creating *franken-stacks*, or "a collection of disparate tools that require work arounds to talk to each other" (Bartolacci 2019). *Franken-stacks* lead to unutilized technology and increased barriers of new technology. Retrospectively, it is simple to identify franken-stacks, but preemptively determining a sales-stack's latent character traits to gain sales-stack cohesiveness and prevent over investment presents a challenge. Very few studies have looked at sales technologies as an adaptable totality of all utilitarian technological resources accessible by the salesforce. That is, most research holds sales technology as a single constant focal stimulus. Academic research has considered, for example, email (Karahanna and Straub 1999; Straub 1994), spreadsheets (Mathieson 1991; Venkatesh and Davis 1996), eCommerce (Gefen and Straub 2000), and computerized models (Lu et al. 2001) as single pieces of technology adoption; none look at the entirety of the sales-stack or the interactivity among technologies.

The current research addresses the premise that sales technologies are not siloed away from other technologies but interplay amongst one another. By understanding the perceived effectiveness of sales-stacks based on latent characteristics of the aggregate sale technologies, organizations can insightfully augment necessary technologies without disturbing the equilibrium of the salesforce workflow. Prior research has brushed the idea of understanding salespersons technological needs like the technology acceptance model (TAM) or expansion era (Lee, Kozar and Larsen 2003). As well as subjects itself to additional frameworks of complimentary acceptance models like Theory of Reasoned Action (Fishbein and Ajzen 1975; Jones, Sundaram and Chin 2002), Innovation Diffusion Theory (Rogers 1983, Moore and Benbasat 1991), and Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003). However, none of the mentioned above, focus on how the technology interacts among itself and the salesperson. Building off the indigenous theory of sales-stacks this research answers the call for operationalizing sales-stacks.

Previous Measures

Technology Acceptance Model

The technology acceptance model (TAM) was developed to evaluate the acceptance of information systems based on perceived usefulness and perceived ease of use (Davis 1985). Since the seminal articles by (Davis 1985, 1989) researchers have leveraged the TAM to encompass numerous information systems and technologies. Chronological growth of TAM research demonstrates that the model has evolved through five progressive eras of transformation (Lee, Kozar and Larsen 2003). Prior to a few decades ago most research grounded by TAM looked at validating and extending the model to include assorted contexts. The validation period supported that the measures for perceived usefulness and perceived ease of use should be grouped separately to best predict and explain technology acceptance (Davis and Venkatesh 1996).

During the extension and elaboration phase, TAM expanded to include external variables such as individual, organizational, and task characteristics (Agarwal and Prasad 1999). Additionally, boundary conditions were identified such as culture, gender, task, and user type

(Adams et al. 1992). TAM II elaborates to account for subjective norms and cognitive instruments (Venkatesh and Davis 2000). The development of the technology acceptance model played an integral role in furthering the technology literature; however, no delineation looks at the characteristics of the collective technology as a whole to understand how salespeople perceive the effectiveness of their tools. Current adoption models have solely looked at the characteristics of sales people to understand how each variable affects adoption (Blunt, Wang and Schoefer 2016). Some constructs boarder sales technology characteristics like compatibility (Moore and Benbasat 1991), technology readiness (Parasuraman and Colby 2015) and risk (Walker, Craig-Lees, Hecker and Francis 2002). In each case, these variables are self-reported measures of how salespeople believe they are compatible and ready to use the technology. Not, if the technology will be compatible or risky integrating with current technologies and systems. A perceived sales-stack effectiveness scale will allow organizations to better assess whether the integration of new technology will cohesively work with current systems.

Perceived versus Objective Effectiveness

Firms invest large sums of money into the investment of sales technology to aid their salesforce. However, many firms have failed to track the objective outcomes of their investments post-implementation (Erffmeyer and Johnson 2001). Research between whether sales technology adoption leads to increased sales performance is scarce and remains an ongoing theoretical debate (Jelinek, Ahearne, Mathieu and Schillewaert 2006).

Technology Leads to Performance

The idea that technology does not lead to better performance grounds itself in the ideation that high performers are more likely to adopt new technology, therefore, whether they had the technology or not they would still be a high performer (Leonard-Barton and Deschamps 1988). High performers intrinsic characteristics make them more inclined to adopt new technology as opposed to low performers tend to need a manager to force technology upon them. Contrary, it is reasonable to infer those low performers may be blinded by their lack of success that they resort to over compensating, or working harder, rather than adopting a streamlined solution.

Many articles have shown that reliance on new technology does lead to increased performance. For example, sales technology not only impacts salespersons performance but also the mannerism of partnering teams within the organization (Rivers and Dart 1999). When a sales team implements technology a halo effect aids cross-functional teams as well. Furthermore, salesforce automation positively improves sales performance (Jelinek, Ahearne, Mathieu and Schillewaert 2006). Sales stacks are designed to streamline a salespersons tool to alleviate internal processes and allowing them to focus on external relationships and performance. Salespersons do not have an option to choose whether they will or will not adopt the company's sales stack because it is the internal resources an organization possess. Thus, with the exception of augmenting from their own personal resources, the salesperson is stuck with the organization's technology. In the process of putting a sales-stack together, the organization's main focus is not whether they can attain salespersons buy-in, but rather the focus is on correctly layering or stacking technologies to ensure technical performance.

Subjective versus Objective Performance

Subjective measures have widely been used to proxy objective measures in sales research (Dawes 1999). Many external factors can impact the decision for researchers to opt towards implementing subjective measures over objective measures. Managers are less inclined to disclose actual firm performance because of the desire to maintain confidentiality (Dess and Robinson 1984). Furthermore, subjective measures may be more appropriate to use when looking at cross-industry samples. For example, if a researcher is looking at cross-industry profits, a subjective answer could help control for the fluctuation of cross-industry characteristics. The current research follows the inclination that subjective measures equate to objective measures grounded by past findings. (Evanschitzky, Eisend, Calantone and Jiang 2012; Wall, Michie, Patterson, Wood, Sheehan, Clegg and West 2004; Dawes 1999).

Development of Perceived Sales-Stack Effectiveness Scale

Study Overview

Following typical psychometric scale development and validation procedures (see Hair et al. 2019; Rutehrford, Boles and Ambrose 2019), the construct scale development process first starts with a working definition. For this measurement, effective sales-stack perceptions are defined as:

the aggregate portfolio of technologies that provide a powerful, connected, easy-to-use experience for every sales role.

The sales literature offers multiple scale developments that provide a foundation for developing, validating, refining and confirming robust measures. Drawing on adaptive measurement items from the technology-usage scale (Engle and Barnes 2000), the adaptive-selling scale-ADAPTS (Spiro and Weitz 1990), and the technology acceptance model's (TAM) scales for ease of use and usefulness (Davis 1989). Additional measures of data value and other Vs of modern data (Chefor 2020), based off of qualitative data collection methods are added. Standard scale development procedures (see Hair et al. 2019) call for refinement and confirmation of the scale, including the observable characteristics that comprise of latent factors underlying overall sales-stack performance.

Unit of Analysis

Sales-stacks are predominately used by the salesforce to help with their daily responsibilities. In order to test the perceived effectiveness of the sales-stack, samples were constrained to B2B salespeople over the age of 18 that had at least two years of sales experience. Additionally, participants are qualified as part of the salesforce if they work under the sales organization of their company. Some examples of sale titles that fall into this category but are not limited to: sales analyst, key account manager, national account manager, director of ebusiness, V.P. of sales, sales coordinator, among other terms. While it is conceivable that sales-stack effectiveness could be construed at a workgroup or organizational level, the scale development begins by considering sales-stack effectiveness as an individual-level construct.

Research Method

Step 1

A multistage approach is used to develop item measures and test the overall fit of the measurement model (Babin, Boles and Robin 2000; Hair et al. 2019; Anderson and Gerbing 1988). Table 6 describes the samples collected during each stage of the process. The first stage involves the development of items that encompass a sales-stack. As alluded above, scales that loosely encompass effective technology aid in the development of the item pool. However, ten in-depth open-ended interviews were conducted with salespeople, to better understand the intricate details of a successful sales-stack. These interviews probed salespeople on how their organizations technologies interact with one another and the usability or lack thereof when used by their organization. Interviewees were strategically selected to ensure a broad range of industries and experiences, in turn making the developed measure universal across all sales related contexts. Sales employment history ranged from 4 to 24 years, current organizational tenure ranged from 6 months to 7.5 years, and current organizational size ranged from 106 to 263,000 employees[3].

[3] Table 2. provides descriptive information of the interviewees

Semi-structured interviews started in the same manner of having interviewees describe and explain the technologies they use and how they use them in a typical work day. For example, one interviewee said the first task they do when getting into work is to pull their sales report and inventory levels for prior day. Follow-up, questions were asked to better understand the technological system the salesperson was using, focusing on the difficulty of using the system, the flow of information in and out of that system, the necessity of the technology to complete their job and hypothetical changes they would make to the technology. This process was repeated until the interviewee completed their entire workday. On average the interviews lasted a total of 60 minutes. A total of 120 potential sales-stack items were generated from this process.

Table 6. Data Collection and Methodology for Multistage Scale Development

	Step 1	**Step 2**		**Step 3**				**Step 4**
Data Collection	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
# Of Items	0	120	112	88	47	44	20	14
Sample	Sales Professionals	Expert Judges	Sales Professionals	LinkedIn Sales Networking Groups$^{\$}$	LinkedIn Alumni Network*	LinkedIn Alumni Network*	Online Panel (Salespeople)$^{+}$	Professional Panel (salespeople)$^{++}$
Sample Size	10	5	3	150	71	194	145	280
Method	Qualitative Interviews	Item Matching	Item Matching	Descriptive Statistics	Descriptive Statistics	Descriptive Statistics & Preliminary PCA	PCA & Preliminary CFA	PCA & CFA
Items Removed	n/a	8	24	41	3	24	6	n/a
Summary	Initial ideation of items developed based off qualitative interviews of sales experts	Sample dichotomously rated items for sales-stack or franken-stack	Sample rated for sales-stack or franken-stack; rated each item *(1 = does not match, 2 = somewhat matches, 3 = matches perfectly)*	Sample rated items (1= strongly disagree; 7 = strongly agree) about their current sales-stack. Skewed items were dropped	Sample rated items (1= strongly disagree; 7 = strongly agree) about their current sales-stack. Skewed items were dropped or reworded	Sample rated items (1= strongly disagree; 7 = strongly agree) about their current sales-stack. Skewed items were dropped or reworded. 3, 4, and 5 construct measures were examined	Sample rated items (1= strongly disagree; 7 = strongly agree) about their current sales-stack. 3 and 4 construct measures were examined. Borderline items were reworded or dropped	Sample rated items (1= strongly disagree; 7 = strongly agree) about their current sales-stack. 3 dimensions were validated and confirmed

NOTES: $^{\$}$At time of survey launch no participants shared mutual groups with either LinkedIn Alumni Network. *Two geographically different networks were chosen to discourage overlap of samples. Current job title was verified to be in a sales role. $^{+}$Preliminary study (n=898) conducted to make sure participants were in sales. Sample was randomly selected from valid participants. $^{++}$Panel manager validated sample.

Step 2

Next a panel of five expert judges was presented the definition of sales-stack (*the aggregate portfolio of technologies that provide a powerful, connected, easy-to-use experience for every sales role)* and franken-stack (*a collection of disparate tools that require work arounds to talk to each other)* along with the generated items from step 1. The expert judges were then asked to mark whether each item matched the definition of a sales-stack or franken-stack. The expert judges did not agree on eight of the items, which were dropped from the next stage.

A second round of expert judges, who are also current sales professionals, was given the remaining 112 items and tasked with marking whether the item matched the definition of sales-stack or franken-stack. Additionally, each judge independently rated each item on the basis of how well it indicated the chosen definition (1=*does not, 2=somewhat, 3=very much 4=I have no idea)*. Items that were not in agreeance with all three judges were dropped from the analysis. Judges also paired duplicate items on the basis of similar content among the items. These items were then evaluated to determine if one of them could be removed from the item pool. In total 24 items were removed. Step 2 acts as a screener in removing items that lack content validity in that they don't reflect the construct of interest. In total Twenty-two items were eliminated in this step.

Step 3

To eliminate potential ceiling and floor effects and evaluate item wordings a preliminary exploratory effort was taken. One-hundred and fifty salespeople from various LinkedIn sales networking groups were recruited and asked to respond to the remaining 88 items on the level of agreement (*1 = strongly disagree to 7 = strongly agree*) about their own sales-stacks that they use. Histograms were generated for each item. Dramatically, skewed items were either dropped or reworded. The removal of skewed items (*on the basis of descriptive statistics)* reduces the possibility of extreme loadings that potentially distort the covariance structure (Babin, Boles and Robin 2000; Nunnally 1978). No items' overall content was altered in this process. Adjectives were either altered to adjust the mean response in future stages of the process or the item was dropped completely. For example, "*It would be difficult for my organization to achieve its goals without the support of my organization's sales-stack"* was altered to *"It would be impossible for my organization to achieve its goals without the support of my organization's sales-stack."* Anything beyond the scope of an adjective change was dropped from future analysis. A total of 41 items were dropped.

This process was repeat once again with the remaining 47 items. A new sample, this time from a LinkedIn Alumni network, was collected. Participants were screened to make sure their current job is in sales and that they weren't part of the previous sales networking group. Once again descriptive statistics were examined dropping or rewording skewed items. Three items were dropped in this stage.

A third iteration of this process was conducted with one hundred and ninety-four salespeople who were recruited though a different alumni network. This new alumni network was strategically chosen to be geographically distant from the first network to discourage overlap within the samples. Once again participants were screened to make sure they are currently employed in a sales role at their organization, along with not being part of the previous sales networking group. The descriptive statistics and histogram plots were once again scrutinized to ensure prior rewordings corrected once heavily skewed items or items were dropped from further analysis. An additional preliminary principal component analysis (PCA) was conducted to look at three, four, and five component structures. Low loading items that were borderline among all three structures were once again either reworded or dropped. Twenty items remained after this stage.

A fourth iteration of this stage was conducted with the remaining twenty items. This time, Prolific, an online panel, was utilized. A pre-screener was selected to have the survey only sent to business professionals. From there a preliminary survey was sent out asking respondents about their professional background, current employment and demographic data. The responses were then compared to the answers that participants provided to Prolific when they signed up to be part of the survey pool. A total of 898 responses were collected. Respondents whose answers did not match the original data when they signed up or were not currently working in a sales profession were dropped. A second survey containing the twenty scale items was then sent to the panel of respondents. Once again, professional background, current employment and demographic data was compared to both the data they provided to Prolific and the preliminary survey. In total 145 respondents answered the Likert items from *1-strongly disagree* to *7-strongly agree* about the sales-stack they use in their organization.

Principal component analysis was used to provide a preliminary signal of scale dimensionality and to eliminate items with low interitem correlations. These results were used to silo items for further confirmatory analysis in the next step. Principal component analysis utilized in an intermediary stage allows for item reduction and clarification of dimensionality (Netemeyer, Boles, and McMurrian 1996, Reidenbach et al. 1991). Using a scree plot the initial principal component analysis suggests a three-factor or four-factor solution. The three factors account for 65.51 percent of the cumulative total variation among items while the four factors account for 71.40 percent. Table 7 provides the item loadings and descriptive statistics. Items not achieving at least .5 loading on any component were dropped. Content from the fourth item seemed to be captured within the other factors and was dropped to reduce repetitiveness. Lastly, the strategic decision to remove the word *sales-stack* from all items and replace it with *portfolio of technologies* was decided to make the scale more universal for future research.

Table 7. Step 3 Descriptive Statistics and Principal Component Analysis Results (varimax loadings)

Item	*Description*	F_1	F_2	F_3	F_4	*M*	*SD*
e1	My company's sales-stack helps me effectively plan selling activities.	0.871				5.27	1.13
e2	I get more work done because of my organization's sales-stack.	0.835				5.16	1.29
e3	I make smarter decisions because of my organization's sales-stack.	0.865				5.05	1.31
e4	I feel more confident in my decisions because of my organization's sales-stack.	0.752				5.16	1.29
e5	My organization's sales-stack allows me to stay extremely organized at the task in hand.	0.704				5.18	1.29
X	It would be difficult for my organization to achieve its goals without the support of my organization's sales-stack.				-0.653	4.95	1.43
X	I use the information from my organization's sales-stack to present to clients.		0.316			4.96	1.45
e8	My organization's systems are all connected to each other.		0.900			4.88	1.69
e9	My organization's sales-stack communicates with all systems within the organization.		0.876			4.67	1.76
e10	My organization's sales-stack connects all systems within the organization.		0.873			4.51	1.77
e11	The information needed to do my job seamlessly flows from each system.		0.783			4.60	1.69
X	I believe the information in my organization's sales system is precisely accurate.		0.496			4.94	1.41
e13	The sales tools I use, interact with one another.		0.783			5.03	1.46
X	I could do my job more easily without using my organization's sales-stack.				0.777	3.13	1.38
X	I would not use my organization's sales-stack if it was not required.				0.801	3.18	1.56
X	Parts of our sales-stack restricts my freedom.				0.604	3.50	1.50
e17	I waste a lot of time working around the bugs in our sales-stack.			0.805		3.39	1.54
e18	Using the system gets in the way of my effectiveness in my job.			0.664		3.11	1.53
e19	Customers sometimes get annoyed by issues caused, because our technologies are inefficient.			0.769		3.76	1.81
e20	I believe my organization's sales force feels hindered by technologies that do not work together.			0.766		3.53	1.69

NOTE: X = item was removed from next scale development stage

Step 4 (main study)

Sample. B2B salespeople were obtained from a professionally managed panel contracted through Qualtrics. Salespeople were required to be currently working in a sales role which is defined as reporting under the sales hierarchy within their organization. A panel project manager was used to ensure objective randomness in selection and screening of respondents (Babin, Griffin, and Hair 2016). In addition to other instructions provided to the project manager, respondents were asked if they consider themselves a frontline employee (i.e., cashier, bank teller, etc.) and what department they currently work in at their organization. If respondents answered yes to being a frontline employee or answered any response other than sales in the organization they were removed. Additionally, respondents were asked to provide their job title (*identifying characteristics of organization were redacted)* and the industry they worked in. If the answers seemed questionable, vague or illogical (*on the subjective basis of a team of internal researchers)* they were removed. Finally, to ensure attention throughout the survey, respondents were asked to select a *Strongly Disagree* and *Agree* Likert choice halfway through and three quarters through the survey respectively (direct attention filters). Respondents were removed by the panel manager if they failed any of the attention checks.

The process resulted in a broad range of 280 B2B salespeople. Respondents ranged from 20 to 80 years of age ($\mu = 50.9$; $\sigma = 13.4$), Sixty-three percent are male (176/ 280), total B2B experience ranged from less than a year (2.5%) to 7+ years (72.9%; $\mu = 22.26$; $\sigma = 10.1$), and tenure with current organization ranged from 1 to 45 years ($\mu = 10.2$; $\sigma = 9.01$). Potential sales-stack perception items were randomized in a survey instrument to prevent order effects. In addition, measures of behavioral job performance (Behrman and Perreault 1982), outcome job performance (Behrman and Perreault 1982), selling effort (Brown and Peterson 1994), malleable data (Peesker et al. 2022), malleable technology (Hunter and Perreault 2007), and sales technology adoption (Davis Bagozzi and Warshaw 1989) were collected to later test nomological validity.

Results

Initial Dimensionality

Once again, principal component analysis was used to provide a preliminary signal of scale dimensionality and check for items with low interitem correlations. These results were used to silo items for further confirmatory analysis. With the reduction of items, the scree plot analysis suggests a three-factor solution. The three factors account for 81.8 percent of the cumulative total variation among items. No items were below .5 loading on any component, suggesting no items should be dropped.

The PCA loadings (following varimax rotation) and descriptive statistics for the 14 items are provided in table 8. As can be seen the majority items lie near the scale midpoint (3-5 on a 7-point scale). The item expressing the highest average agreement is "My organization's portfolio of technologies effectively support my selling activities." and the item with the lowest level of agreement is "Customers sometimes get annoyed by issues caused because my organization's technologies are inefficient." The factors have a conceptually plausible interpretation. Factor 1 consists of items indicating *support* with regards to how much the sales-stack supports the salespersons activities. Factor 2 indicate *connectivity* of how well the sales-stack connects to other technological systems in the organization. Item loadings on factor 3 suggest a *hinderance* on the external factors around the organization when sales-stack is less than efficient, indicative of franken-stack perceptions. This dimensionality is generally consistent with the indigenous theory of sales-stacks mentioned above.

Confirmatory Factor Analysis

Dimensionality and validation. Confirmatory factor analysis (CFA) was used to provide a more thorough validation. Table 9 shows CFA results using the 14 items constrained consistent with the factor structure from the principal analysis. The model chi-square 142.8 with 74 degrees of freedom (*p=.000)*, the model Goodness of Fit Index (GFI) is .93, the Comparative Fit Index (CFI) is .98, and the root mean square error of approximation (RMSEA) is .058. These statistics support the measurement model overall fit (Hair et al., 2019).

Other results support the constructs' convergent validity. Construct reliability estimates range from .96 (ξ_1- support) to .88 (ξ_3- hinderance), and the variance-extracted estimates range from .88 to .66. Furthermore, all factor loadings are highly significant (P<.001), suggesting adequate scale convergence (Anderson and Gerbing 1988). All variance-extracted estimates are greater than the square of the correlation between factors suggesting discriminant validity. Overall, the fit statistics support the scales psychometric properties and thus, the construct validity of the sales-stack effectiveness scale.

First and second-order model. The three dimensions display discriminant validity, but they are related to one another. Figured 5 displays correlations of support <-> *hinderance (-.421), support* <-> *connectivity (.716)* and *connectivity* <-> *hinderance (-.529).* Theoretically, one could envision a more abstract representation where sales-stack effectiveness exists as a higher-order factor with the individual first-order factors as its indicators.

Psychological perceptions fall into an area where latent measures are studied using a varying degree of abstract depending on the research question. Bagozzi and Heatherton (1994) detail out scenarios where a first or second order model can utilize the same latent constructs and be psychometrically sound measure. Given that certain research may be interested in single construct of sales-stacks or the aggregate of all dimensions a psychometric analysis was undertaken addressing an omnibus second order factor (see Figure 5). Constraints were placed on the covariance structure consistent with a second-order factor model. The average variance extracted (AVE) for support, connectivity and hinderance is .817, .793, .655 and construct reliability .96, .95 .88 respectively. These results support the convergent validity of using the sale-stack perception scale as a second order model. The higher order model produced an exact match of fit statistics making a case that the measure can be used in both a first and second order model (a mathematical byproduct of three-factor models).

Discussion

Step 6, in Hunt’s (2020) seven-step process of theory development is, *testing the foundational premises*. The perceptions of sales-stack effectiveness scale provide a stepping stone to empirically test the theory of sales-stacks proposed in chapter 2. In order to close the gap between sales technology and sales-stacks a new measure is needed to accommodate the disseminating characteristics between the two concepts. Sales technology has been measured in numerous ways, most notably, access, analyze and communicate (Hunter and Perreault 2007). While this, among others, are valid ways to measure sales technology; the scales are predominately based on the salespersons singular use of the technology. This leads to the assumption; salespeople need a piece of technology for each task they work on. The indigenous theory of sales-stacks combats this supposition, by proposing that a “stack” of well-connected technologies provide prevailing capabilities. In turn, salespeople reduce their dependence on numerous pieces single use technology and exchange it for a cohesive platform that supports all of the tasks they work on (sales-stacks). Sequentially, since sales-stacks contain all the technology a salesperson needs for their role, a new measure is needed to understand how the technologies interact amongst each other and the salesperson, as opposed to just the salesperson.

The three dimensions of support, connectivity and hinderance capture the balance between the technologies working together with one another, while also supporting the salesforce. Connectivity, encompasses the notion that the technologies that make up the stack should be seamlessly integrated in order for them to be a single cohesive platform. Support, captures the idea that the sales-stack provides everything a salesperson needs to aid in their functional role. Hinderance, is the antonym of the two in that it actually slows down the stack, salesperson or both. High hinderance could be an indicator that the sales-stack is actually a franken-stack, in that it hampers the salesforce. Coinciding with this successful scale development, this research contributes by supporting the proposed foundational premises of sales-stacks.

The scale development process begins as an exploratory methodology, in that there are no predetermined factors when the initial items are developed. Interestingly, the three confirmed dimensions align with the six foundational premises. The first dimension, connectivity, directly supports FP1 and FP2 in that an effective sales-stack is well connected. The second dimension, support, contributes to the further exploration of FP3, FP4, and FP5. As the technology from sales-stacks disseminates through an organization and industry, salespeople spend less time trouble shooting their own technology and more time supporting their customer’s needs. The third dimension, hinderance, acts as a precursor when progressive technological tools are not maintained (FP6).

Results also show that either a lower order or higher order representation of sales-stack perceptions of effectiveness is psychometrically sound and theoretically useful. Allowing for the measures to work in a first or second order manner expands the practicality of the scale (Babin, Boles and Robin 2000). Researchers interested in specific relationships between dimensions or looking to test precise attributes of sales-stacks may employ the first order model. On the other hand, researchers interested in omnibus predictions can employ the higher representation. To further test this notion and establish evidence of nomological validity an integrative model is introduced in the next chapter.

Table 8. Descriptive Statistics and Principal Component Analysis Results (varimax loadings)

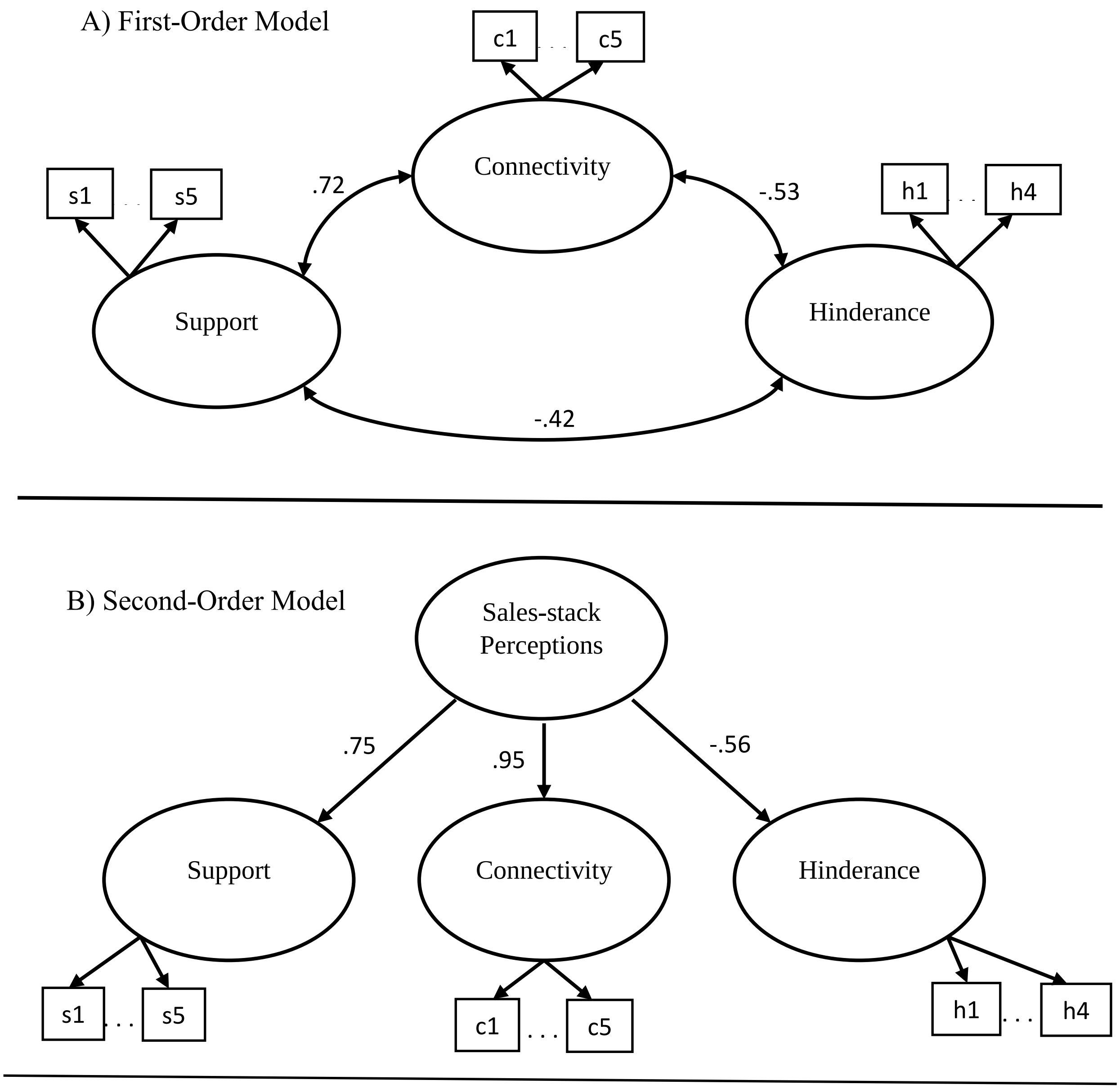
Item	*Description*	F_1	F_2	F_3	*M*	*SD*
e1	My organization's portfolio of technologies effectively supports my selling activities.	0.862			5.22	1.34
e2	I get more work done because of my organization's portfolio of technologies.	0.857			5.00	1.42
e3	I make smarter decisions because of my organization's portfolio of technologies.	0.886			5.02	1.38
e4	I feel more confident in my decisions because of my organization's portfolio of technologies.	0.849			4.98	1.43
e5	My organization's portfolio of technologies allows me to stay extremely organized at the task in hand.	0.815			5.06	1.42
e6	My organization's portfolio of technologies is all connected to each other.		0.831		4.55	1.64
e7	My organization's portfolio of technologies communicates seamlessly with one another.		0.865		4.38	1.57
e8	My organization's portfolio of technologies connects with each other to act as one.		0.823		4.43	1.57
e9	The information needed to do my job flows seamlessly between all technologies within my organization.		0.792		4.51	1.54
e10	The sales technologies I use interact perfectly with one another.		0.791		4.44	1.59
e11	I waste a lot of time working around the bugs in my organization's technology.			0.838	3.42	1.61
e12	Using my organization's portfolio of technologies gets in the way of my job effectiveness.			0.820	3.38	1.65
e13	Customers sometimes get annoyed by issues caused because my organization's technologies are inefficient.			0.844	3.31	1.62
e14	I believe my organization's sales force feels hindered by my organization's technologies that do not work together.			0.807	3.60	1.72

Table 9. Standardized Confirmatory Factor Analysis (CFA) Loading Estimates

Item	*Description*	*Support* $\xi 1$	*Connectivity* $\xi 2$	*Hinderance* $\xi 3$
s1	My organization's portfolio of technologies effectively supports my selling activities.	0.91		
s2	I get more work done because of my organization's portfolio of technologies.	0.90		
s3	I make smarter decisions because of my organization's portfolio of technologies.	0.90		
s4	I feel more confident in my decisions because of my organization's portfolio of technologies.	0.91		
s5	My organization's portfolio of technologies allows me to stay extremely organized at the task in hand.	0.90		
c1	My organization's portfolio of technologies is all connected to each other.		0.88	
c2	My organization's portfolio of technologies communicates seamlessly with one another.		0.93	
c3	My organization's portfolio of technologies connects with each other to act as one.		0.88	
c4	The information needed to do my job flows seamlessly between all technologies within my organization.		0.89	
c5	The sales technologies I use interact perfectly with one another.		0.87	
h1	I waste a lot of time working around the bugs in my organization's technology.			0.89
h2	Using my organization's portfolio of technologies gets in the way of my job effectiveness.			0.77
h3	Customers sometimes get annoyed by issues caused because my organization's technologies are inefficient.			0.76
h4	I believe my organization's sales force feels hindered by my organization's technologies that do not work together.			0.81
	Variance extracted	0.82	0.79	0.66
	Reliability	0.96	0.95	0.88

NOTE: The item abbreviations represent the scale interpretations (s = support, c = connectivity, and h = hinderance).

Figure 5. Perceptions of Sales-stack Effectiveness Model



NOTE: All φ coefficients (Frame A) and loadings (Frame B) are significant $p<.05$

IV. SALES-STACK EFFECTIVENESS STRUCTURAL MODEL

Introduction

Sales technology is a catalyst that can convert a good sales person into a great salesperson. Judgements on what technologies to implement have are not always been the decision of the sales force but an initiative set by top level management and executive teams. While the intentions of these decisions are made with the salesperson's best interest in mind, the outcome has shown lack-luster results. A call for research has set a priority on how to integrate new technology into the current sales structure (Singh, Flaherty, Sohi, Deeter-Schmelz, Habel, Meunier-FitzHugh, Malshe, Mullins, and Onyemah 2019). On the surface it is easy to look at a single piece of technology and understand the perceived benefits. However, with each technological addition to the salesforce tool box, integration becomes more of a challenge. Numerous models have looked at the adoption of sales technology such as Technology Acceptance Model (TAM) (Davis 1989), Theory of Reasoned Action (TRA) (Thompson, Higgins, and Howell 1991), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis and Davis 2003).

The majority of these models work under the premise that a single technology is being adopted such as database programs (Doll et al. 1998), support systems (Gefen and Keil 1998) and groupware (Lou et al. 2000). Another delinquent characteristic of many of the adoption models, is that only exogenous characteristics are used as focal actors to better understand how technology is adopted. That is, these models look at the sales persons willingness to use the technology, the perceived control of managers and learning curve for the technology. Very few models look at how the new technology integrates with current technology.

Salesforces have become less apprehensive about adopting and using technology but have a growing concern about how the new technology will integrate with the current technology. A single piece of sales technology can impact sales effectiveness (Hunter and Perreault 2007), however, with each technological addition another layer of complexity is added to the salesforce tools box. Sales-stack, stack for short, are the tool box for sales people to do their job. Stacks are the aggregate of all sales technology a salesforce can utilize to achieve their goal. The purpose of this research is to integrate on the technology adoption model along with indigenous theory ideation (Hunt 2020) to understand the characteristics of how new technology can be integrated with current technology to sustain an optimized sales-stack that the salesforce will use.

Background

Grounded in the information technology literature, TAM (Davis 1989) looks at the acceptance of information systems. TAM primarily looks at external factors such as internal beliefs and attitudes about technology. Since the inauguration of TAM twenty-five new external variables have been introduced to the model (Lee, Kozar, and Larsen 2003). However, none of these new variables look at the integrated characteristics of new technology being accepted into existing technology. The closest variable to be added to the model is compatibility (Rogers 1983; Chin and Gopal 1995; Xia and Lee 2000). However, in the context of TAM compatibility is defined as "The degree to which an innovation is perceived as being consistent with existing values, needs and past experiences of potential adopters" (Lee et al. 2003). Once again this looks at the perception of the end users of the technology and not the perceived integration compatibility.

Unified Theory of Acceptance and Use of Technology

Unified Theory of Acceptance and Use of Technology (UTAUT) studies the individual technology acceptance across a variety of settings like organization types, technology types and user groups (Venkatesh, Thong, and Xu 2016). This theory stemmed from TAM in that it looks at exogenous variables to better understand the adoption and use of a single technology. Many different types of technologies have been used within this framework such as online shopping (Lian and Yen 2014), agile information systems (Hong et al. 2011) and E-learning in the work place (Yoo et al. 2012). Similar to TAM, UTAUT lacks the endogenous aptitude to help understand how new technology will integrate into the current sales technology environment of an organization. It has become overly apparent that within the sales literature a need for a new theory to better explain how the integration of new technology can impact a sales force.

Indigenous theory

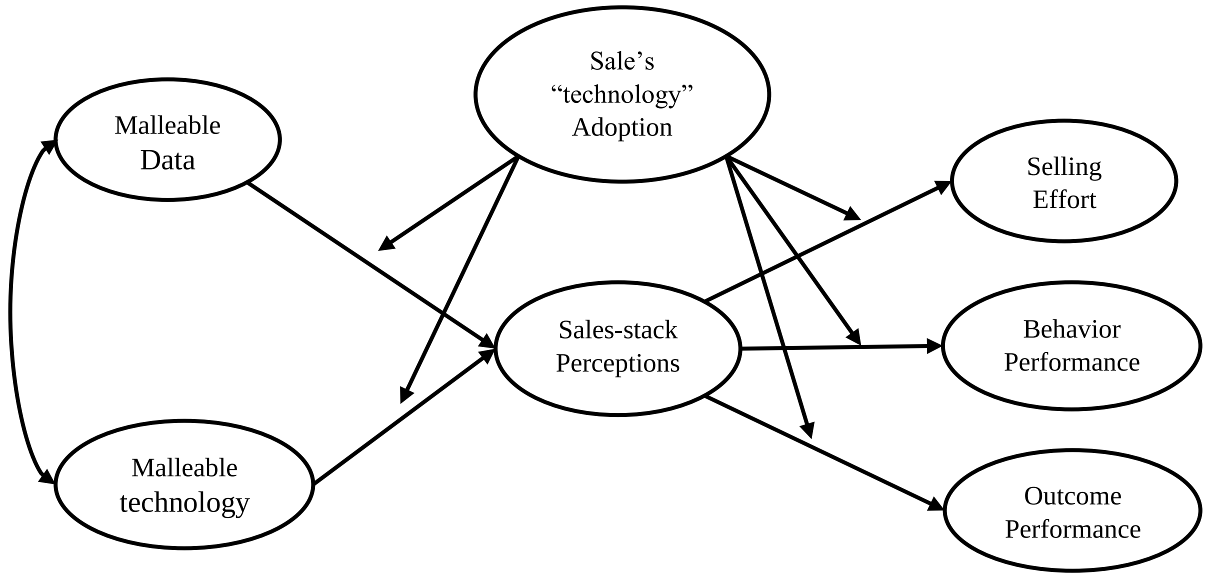
Marketing as a discipline lean too heavily on the theories of other disciplines (Hunt 2020a; 2020b; Varadarajan 2020). As alluded to above technology acceptance models stem from the information technology stream and cross over into the marketing discipline. Marketing researchers have called for more indigenous theory to be developed to help support the discipline (Hunt 2020). A seven-step approach has been advised when developing a new theory: 1) identify the problem 2) identify gap within the current theories 3) addressing insight into how to close the gap 4) develop foundational premise of new theory 5) review development foundation 6) test foundations 7) revise premise within future publications. To recapitulate, section one and two fulfills steps 1-4 in the indigenous theory process. Current research looks predominately at single use technology while organizations technology is strongly intertwined amongst the systems causing a need for a new theory that encompasses all of an organizations sales technology. Thus sales-stack is introduced and defined as the *aggregate portfolio of technologies that provide a* *powerful, connected, easy-to-use experience for every sales role.* Section one concludes with developing six foundational premises to guide the continuation of research in sales-stacks. Section two, acts as a continuation of Hunt's (2020) seven step process, specially addressing steps 5 and 6. In the section a valid measure for sales-stack perceptions is proposed, refined and confirmed to be a working measure in both a higher and single order model. The current research section is a continuation of step 6, in testing the nomological validity of the sales-stack perception scale, while also looking at antecedents and outcomes to sales-stacks.

Hypothesis and Proposition Development

There are two under lying difficulties when looking at current technology adoption models. 1) The models only look at a single piece of technology being adopted but do not look at the of current technology an organization already possess. 2) The models look at the exogenous factors of adoption but are deficient when looking at endogenous characteristics of the sales technology environment.

To better understand the adoption of technology a theory needs to look at the integration of sales technology into an organizations sales-stack and how it will affect the end salesforce. The proposed model (see figure 6) allows for organizations to better understand the characteristics that are needed to maintain an optimal sales-stack that allows the salesforce to achieve their goals.

Figure 6. Conceptual Framework of Sales-stack Perceptions



Malleable Technology

Malleable technologies are those that can produce results for the specific purpose for which they were acquired (Hunter 2019). Salespeople are becoming more tech savvy, which is increasing their creativity to use technologies to accomplish goals outside their original means. The idea of working smarter, not harder, has taken on new meaning as salespeople look to increase productivity while maintaining meaningful relationships with their customers. Malleable technology allows users to manipulate and modify capabilities as part of the usage (DesAutels 2011). Malleability forces salespeople to adapt their professional routines to coincide with the technology their organization provides. The diffusion of malleable technologies act as an enabler to empower salespeople to take on new challenges that they couldn't before (Schmitz et al. 2016). Intuitively, malleable technology seems incrementally beneficial to be able to adapt technologies for the precise purpose a salesperson needs. However, *too much* use and emphasis on aspects of technology has been shown to reduce productivity (Engle and Barnes 2000).

Malleability can, in turn, become more of a nuance than a benefit. If every time a salesperson wanted to create a new sales presentation, he/she had to start off by making a new template, a lot of time would be wasted resulting in an inefficient system. When firms over invest in technology sales people waste time replicating processes that could be standardized. As sales technology usage increased performance is hindered in an inverse U shape (Ahearne, Srinivasan and Weinstein 2004). That is, technology only increases sales performance until a certain point, then after inflection, technology can hurt performance. As alluded to above, this supports the idea that franken-stacks can be detrimental to an organization (Bartolacci 2019). If too much technology builds on top of each other and fails to work cohesively together, salespeople have to spend a relatively longer time using multiple systems, hampering their performance. The main point of a sales-stack is to streamline the salesperson's work. Efficiency comes from cutting back on unneeded technologies and leaving only the necessary technologies available. When a sales-stack can layer all necessary technologies into a single platform to support the salesperson, the salesperson will spend less time using it and more time selling. Sales-stacks allow for the optimal amount of sales technology usage by the salespersons to land in the sweet spot between usage and performance.

H1: Large amounts of malleable technology is negatively related perceived sales-stack effectiveness

Referring back to the indigenous theory, namely FP2[4], when an organization has excessive amounts of malleable technology, the sales-stack effectiveness becomes hindered because there is a higher probability the stack is transforming into a franken-stack. Increased technology means more systems must talk to each other, which entails more potential issues to go wrong. Contrary, if the sales-stack is properly aligned with the salesperson's procedures and correctly united with compatible technologies the sales-stack should alleviate all concerns of the over use of technology.

Malleable Data

Firms use sales forecasting as grounds to help project new product success and overall revenue. These projections help the firm develop overall marketing strategies, create demand forecasts and generate strategic business decisions (Marshall, Dockendorff and Ibanez 2013; Shi, Bigdeli and Li 2015). When firms can culminate precision in their sales forecasting model, they can optimize strategic plans mitigating economic loss (Mentzer and Bienstock 1998). Many researchers have taken on the task in developing accurate forecasting models to aid in business decisions. The Bass model (Bass 1969) and extensions of it like the Norton model (Norton and Bass 1987) and contingent diffusion model (Peterson and Mahajan 1978) are commonly used for product sales forecasting and have been applied to IT technology (Barnes, Southwell, Bruce and Woodhams 2014). Within these models' simultaneous factors (internal and external coefficients) are taken into consideration. Additionally, research has shown that two primary factors influence consumer purchase decisions (Fan, Che, and Chen 2017). The first is recommendations from consumers who have purchased the product and the second is influential advertisements through mass media. Sentiment analysis has been increasingly popular among researchers to capture

[4] FP2 - Idiosyncratic and compatible sales technologies are the building blocks of an effective sales-stack

online reviews and eWOM (Kozinets, De Valck, Wojnicki, and Wilner 2010, Yu, Li, Huang and An 2012).

Sales forecasting can be defined as “the set of methodologies and techniques used for acquiring and transforming raw data into structured information for analytical purposes” (Jimenez, Sanchez, Garcia, Sciavicco and Miralles 2017). Sales forecasting is only one aspect of a sales-stack. Malleable data allows for more data points to be collected. It no longer just looks at sales specific data but takes into account product launch budgets, sales channels, sentiment about the company as well as products. On its own, malleable data does not do much for a salesperson because it is too much information for a salesperson to analyze and act on. When used as an input for a sales-stack the system can analyze and proactively nudge the salesperson to act upon an upcoming opportunity.

H2: Large amounts of malleable data is positively related perceived sales-stack effectiveness

In other words, the more data a salesperson has the more overwhelmed they will become trying to analyze it on their own. Salespeople want to use all the data at their exposal; however, they can’t spend too much time analyzing because they need to be out in front of their customers. Since an effective sales-stack is seamlessly connected (FP1), it allows the data to be analyzed quicker, than if a salesperson did it on their own. Therefore, a salesperson will have higher perceptions of a sales-stack, because it can provide analyses that the salesperson otherwise wouldn’t be able to do.

Perceptions of sales-stack effectiveness impact on performance

Research on the use of sales technology and the effects it has on salesperson performance has been well documented throughout the literature (Hunter and Perreault 2007; Singh et al.

2019; Ahearne et al. 2007; Peltier et al. 2013). Salespeople's ability to meet sales goals is greatly improved by technology solutions (Hunter and Perreault 2006; Rodriguez and Honeycutt 2011). Although salespeople are in control of how they interact with their clients, there are many external factors that can impact a salespersons performance outside of the technology that they use (Zallocco, Pullins, and Mallin 2009). Since, it is tough to control for all external factors it is recommended to examine both behavioral and outcome-based performance measures (Miao and Evans 2007). Behavioral based outcomes focus on the interactions between the salesperson and their customers (Behrman and Perreault 1982). On the other hand, outcome performance, focuses on quantitative performance the salesperson achieves. Subjective measures, have widely been used to proxy objective measures in sales research (Dawes 1999). In instances when organizations want to protect strategic advantages, such that of technological capabilities, respondents are less inclined to give objective answers (Dess and Robinson 1984).

Sales-stacks are the technological epicenter for a salesforce. In an effective sales-stack all sales related tasks flow through the stack cohesively (FP1, FP2)[5]. A well-connected stack alleviates pressure from pulling data and reports manually and provides the salesperson with intricate insights to equip them in the selling process. The additional time that a salesperson receives by having an effective sales-stack can be refocused into their selling efforts (Brown and Peterson 1994). Intuitively, the more time, along with, strategic information a salesperson has the better they can focus their energy into selling and relationship building with their customers.

H3: Perceived sales-stack effectiveness positively related sales outcomes

[5] Rationale based on the foundational premises of the indigenous theory of sales-stacks in chapter 2

Mediation of effective sales-stack perceptions

Prior research has found the relationship between technology and salesperson performance is not always direct (Hartline et al. 2000). In cases where the technology is not cohesive, the technology can actually begin to hinder performance (Ahearne, Srinivasan and Weinstein 2004). In extreme instance the technology is such a burden on the salesforce they will opt out of using the technology, either forgoing reports they may otherwise need or making timely work arounds to understand data insights. The enhanced collection of customer and competitor data has led to improved data quality (Gorla et al. 2010). In today's sales landscape data is power for a competitive salesforce. The more, raw data that can be converted into strategic insights for a salesperson the larger competitive advantage they have.

Effective sales-stacks provide a cohesive solution to gathering, reporting, and utilizing mass amounts of data. Sales-stacks, when effectively, built provide a harmonious balance between necessary technologies a salesperson needs and big data pulled from multiple sources. The connective property of sales-stacks allows for the stacked technologies to pass data along automatically (FP2 and FP4)[6]. That is a perfect sale-stack connects the technologies a salesperson needs, supports the functional role of a salesperson and alleviates burdens (hinderance) that would otherwise be placed on the customer[7]. However, there is no such thing as a perfect sales-stack. With any sales-stack there will always be outside technology or data that isn't compatible with an organizations sales-stack. Therefore, an effective sales-stack has the ability to take large amounts of single use technology (malleable technology) and crunch it down to be useful by the salesperson. Likewise, an effective sale-stack can interpret large amounts of data, that a salesperson otherwise couldn't. In total, an effective sales-stack compresses the

[6] Rationale based on the foundational premises of the indigenous theory of sales-stacks in chapter 2

[7] Connectivity, support and hinderance are the three dimensions pulled from sale-stack effectiveness scale in Chapter 3

constraints that large amounts of unconnected malleable technology and data have on salespeople.

H4: Perceived sales-stack effectiveness mediates the effect of malleable technology on sales outcomes

H5: Perceived sales-stack effectiveness mediates the effect of malleable data on sales outcomes

Moderating Barriers

Sales-stacks are the valve that can make the whole sales process flow fluidly and efficiently. When the sales-stack is optimized, it allows for a salesperson to spend less time trying to trouble shoot internal systems and track down internal data and more time building relationships and pursuing leads.

Implementing sales technology can be a bigger headache than choosing the correct technology. Prior research has split adoption barriers into two categories, internal and external (Buehrer, Senecal and Pullins 2005). In laymen's term, external barriers are implications that are outside the organization. This can be the apprehension of sales people willing to use the technology because they feel like they don't need more technology to do their job. Internal barriers can best be explained by barriers that are internal to the organization. This can best be described as the technological capabilities or lack thereof that prevents technology being implemented.

Most sales literature doesn't call out adoption barriers for sales technology but instead looks at the antecedents for implementing sales technology (Jones, Sundaram, and Chin 2002). Many of these antecedents or barriers are focus on the salesperson's intuition of the new technology. Some examples of these are perceived control (Green and Hevner 2000), user attitude (Ajzen and Fishbein 1980) and personal innovativeness (Agarwal and Prasad 1998). Other research focuses on the internal barriers an organization might face like the support services a company provides when onboarding new technology and the organization innovativeness (Robinson, Marshall and Stamps 2005).

In any case, whether internal or external barriers, push back towards a new system can be detrimental for any new adoption of sales technology. Not only does it take the correct mix of technology layered properly to ensure that the systems communicate with each other. It also takes the complete buy in from the sales force to utilize it. Thus, I hypothesize:

H6: Sales adoption moderates the effect of malleable data on perceived sales-stack effectiveness such that low adopters will display larger effects than high adopters

H7: Sales adoption moderates the effect of malleable technology on perceived sales-stack effectiveness such that high adopters will display larger effects than low adopters

Similar to adoption barriers, research has looked at intention versus infusion barriers. Intention looks at the willingness of a salesperson to use the technology, while infusion looks at the extent a salesperson uses it. For instance, a salesperson might be required to use the new technology so they have high intensions for new technology. However, they might not like the new technology so they have low infusion (Jones, Sundaram, and Chin 2002).

If the salesforce uses the sales-stack based on formalities and not because they see the benefits, the sales-stack becomes under-utilized. While usage has been shown to correlate with sales performance (Ahearne, Srinivasan and Weinstein 2004). Under usage could lead to lack luster sales results, on the basis, that salespeople don’t think the technology lives up to its full potential. Thus, I hypothesize:

H8: Sales adoption moderates the effect of perceived sales-stack effectiveness on sales outcomes such that high adopters will display larger effects than low adopters

Propositions

Few sales force automation projects have been successful on the first implementation (Rivers and Dart 1999; Schafer 1997). When automating a salesforce, it is an extra layer of precise detail and system alignment that is needed to ensure flawless execution. The goal of automation is to prevent the need for salesperson interaction within the system. By removing the salesperson from a system, firms believe costs will be reduced, human error removed, and the sales process streamlined. Large tech and eCommerce organizations have automated back-end systems to accompany the growing demand of manufactures who want to do business with them. Instead of talking to a human buyer at Amazon, organizations are now work through an Amazon portal to set up sales, flash deals, and promotional pricing.

Calls for papers to better understand factors and empirically test salesforce automation continue to gain traction within the sales discipline (Marshall and Michaels 2001; Jones, Sundaram and Chin 2002). It is not the lack of motivation from researchers that is responsible for not pushing the salesforce automation agenda. It is the complexity of collecting data to empirically test feedback loops.

Automotive technology coincides with artificial intelligence and machine learning. In that sense researchers need to continually measure feedback loops to understand how the automation learns from previous sales outcomes. Intuitively this type of data collection seems simplistic, however sales cycles typically run a year. Therefore, researchers need to obtain a sample of almost a decade to understand sales feedback loops. In the proposed model, two feedback loops are proposed based off the sales outcomes when a sales-stack is utilized. While the current research doesn't have the capacity to collect such data. It is hopeful that the two proposed propositions can act as a launch point to continue the development of automation and machine learning literature.

P1: Sales outcomes will positively affect perceived sales-stack effectiveness

P2: Sales outcomes will positively affect malleable data

Research Methodology

Sample

The sample consists of currently employed, U.S. B2B salespeople who were obtained from a professionally managed online panel contracted through Qualtrics. Salespeople were required to be currently employed and not a frontline employee. An assigned project manager was utilized to increase objectivity in selecting and screening respondents and cleaning the initial data set (Babin, Griffin and Hair 2016). In addition to other instructions provided to the project manager, respondents were asked to provide their years of sales experience, the current years of tenure at their organization, the job title they currently hold and the describe the industry they work in. A face validity check was conducted to make sure respondents fit the target sample. If the respondents' answers were vague or described a sales position that reflected a frontline employee they were removed from the sample. Additionally, two manipulation checks were employed to make sure respondents were reading each question. Twice in the survey respondents were asked to select *strongly disagree* and *strongly agree* respectively. Any failed attention checks were removed from the panel manager response.

The process resulted in a sample of 280 B2B salespeople[8]. Respondents ranged from 20 to 80 years of age ($\mu = 50.9$; $\sigma = 13.4$), Sixty-three percent are male (176/ 280), total B2B experience ranged from less than a year (2.5%) to 7+ years (72.9%; $\mu = 22.26$; $\sigma = 10.1$), and

[8] Same sample of salespeople from the CFA in prior chapter were used for structural model analysis

tenure with current organization ranged from 1 to 45 years ($\mu = 10.2$; $\sigma = 9.01$). Later analysis of interactions effects calls to look for differences between high and low sales adaptors. A median split on sales adoption was conducted removing the middle ten percent of the sample to ensure concrete differences between the groups (Iacobucci et al. 2014). Descriptive statistics of the groups can be seen in table 10.

A basic check for common method variance bias was tested by computing the primary eigenvalue across all scaling items. The eigenvalue accounted for 34.27% of the variance in the data, well below the 60% threshold that might trigger further action to deal with the potential of subsequent bias (Fuller et al., 2016). The study design deployed differing scaling approaches for different factors, which works to lower the potential for common methods bias (Hair et al., 2019).

Table 10. Hypotheses Testing – Sample Profile

	Full Model		Low Sales Adoption		High Sales Adoption	
	N	%	N	%	N	%
Gender:						
Male	176	62.9	73	64.6	73	64.0
Female	104	37.1	40	35.4	41	36.0
Age						
18-29	18	6.4	5	4.4	10	8.8
30-39	44	15.7	15	13.3	20	17.5
40-49	59	21.1	21	18.6	24	21.1
50-59	77	27.5	36	31.9	27	23.7
60+	82	29.3	36	31.9	33	28.9
Tenure						
< 2 years	42	15.0	19	16.8	14	12.3
2.0-4.9 years	62	22.1	29	25.7	25	21.9
5.0-9.9 years	56	20.0	19	16.8	27	23.7
10.0-15.9 years	54	19.3	20	17.7	22	19.3
16-19.9 years	10	3.6	2	1.8	3	2.6
20+ years	56	20.0	24	21.2	23	20.2
Sales Experience						
< 1 year	7	2.5	4	3.5	2	1.8
1-6.9 years	69	24.6	22	19.5	31	27.2
7-12.9 years	28	10.0	11	9.7	11	9.6
13-18.9 years	39	13.9	15	13.3	15	13.2
19-24.9 years	40	14.3	20	17.7	11	9.6
25+ years	71	25.4	34	30.1	30	26.3
> 7+ but not specified	26	9.3	7	6.2	14	12.3

Measures and controls

All measures utilize Likert scales drawn from the literature with the exception of sales-stack perceptions which is developed and confirmed as a valid measure in prior chapters. Likert scale response ranged from *1 (Strongly Disagree)* to *7 (Strongly Agree)* except for malleable technology (Hunter and Perreault 2007) which ranges from 1- 7 with endpoints of *Routine* –

Sporadic; Frequent – Infrequent; A Major Emphasis – Not a Major Emphasis; Hesitant – Confident respectively.

Malleable technology consists of a three factor higher order measure (Hunter and Perreault 2007). The factors of access, analyze and communicate have been shown as the three major areas where salespeople utilize sales technology. Malleable data is assessed using a two factor, adapted eight item higher order measure (Peesker et al. 2022). Factor one, measures an organizations possession of data that describes analytics and territory management, while factor two measures the organizations' ability to obtain customer insight data. The two measures make up the wholistic amount of data a sales-stack needs to aid a sales-person in making decisions. Selling effort is measured using a three-item measure (Brown and Peterson 1994). Behavioral and outcome sales performance is measured using a three and four item measure respectively (Behrman and Perreault 1982). Finally, sales technology adoption is measured on an adapted five item measure, curated to see the willingness of salespeople to adopt organizations sales-stacks (Davis Bagozzi and Warshaw 1989). All item measures can be found in Appendix 1.

Concurring, with prior research, control variables include age, sex, tenure, and sales experience were collected. (Epstein et al. 1996; Groza et al. 2016). Differences among individuals, as well as, individuals' organizational experiences when controlled reduce the variability in the dependent measures (Agnihotri, Dingus, Hu, and Krush, 2016). "As a result, the sample becomes more homogeneous, which leads to greater precision in estimation" (p.176).

Results

Measurement Model

Auxiliary Model Validity. A confirmatory factor analysis (CFA) using AMOS 25 is conducted to assess the validity of the theoretical measurement model representing all latent factors and the theoretical links to each factor's reflective indicators. Not only is this test needed as the first step in the two-step process of testing structural models (Anderson and Gerbing 1988), but it also provides a further test of the discriminant validity of the sales stack effectiveness scale. The results indicate a reasonable fit considering the model complexity and sample size (Hair et al., 2019). The model $\chi^2 = 1753.51$, df = 881 ($p < .001$); comparative fit index (CFI) = .92; root mean square error of approximation (RMSEA) = .06. Table 11 presents standardized factor loading estimates for each factor loading as well as the subsequent construct reliability (CR) and average variance extracted (AVE) for each factor. Construct reliability estimates range from .81 to .96, supporting each scale's internal consistency (Hair, Babin, and Krey, 2017). Discriminant validity is assessed by comparing the average variance extracted (AVE) estimates for each factor with the squared interconstruct correlations (SIC) associated with that factor. All of average variance extracted (AVE) are greater than the squared interconstruct correlations, with the exception of sales-stack perceptions and malleable data. This test demonstrates acceptable discriminate validity. The correlation matrix of higher-order variables is presented in Table 12.

Table 11. Scale Item Measurement Properties

	Sales-stack Perceptions (SP)	Malleable Data (MD)	Malleable Technology (MT)	Effort (Eff)	Behavior Performance (BP)	Outcome Performance (OP)
Support	-0.85					
Connectivity	-0.85					
Hinderance	0.53					
Pipeline Mgmt.		0.97				
Customer Insight		0.96				
Communicate			0.83			
Access			0.85			
Analyze			0.93			
Eff1				0.58		
Eff2				0.80		
Eff3				0.89		
BP1					0.73	
BP2					0.75	
BP3					0.78	
OP1						0.75
OP2						0.86
OP3						0.83
OP4						0.82
Variance Extracted	0.58	0.92	0.76	0.59	0.57	0.67
Reliability	0.80	0.96	0.90	0.81	0.80	0.89

Table 12. Correlation Matrix

	Construct	1	2	3	4	5	6
1	sales-stack perceptions	1	**.615**	**.231**	**.134**	**.091**	**.031**
2	Malleable Data	-0.784	1	**.167**	**.079**	**.085**	**.051**
3	Malleable Technology	-0.481	0.409	1	**.104**	**.204**	**.091**
4	Selling Effort	-0.366	0.281	0.323	1	**.314**	**.368**
5	Behavioral Job Performance	-0.301	0.291	0.452	0.560	1	**.578**
6	Outcome Job Performance	-0.177	0.225	0.301	0.607	0.760	1

NOTE: Φ matrix squared are bolded for convenience

Structural model testing

Direct Effects Model. A structural equation model (SEM) is utilized to test the proposed model. After imposing the model-consistent theoretical constraints, the results indicate acceptable fit with the data: χ^2 =1967.34, df = 994, p < .001; CFI = .91; RMSEA = .059. The addition of control variables to the model does not significantly alter any of the hypothesized parameter estimates. Additionally, with the exception of sales experience on the dependent variables, none of the control variables have a significant relationship with the model constructs. Sales experience was an expected relationship with the dependent variables as one of the requirements to be part of the study is to be active in a sales role and one would not expect an unsuccessful salesperson to remain in sales if they have failed in prior years.

Table 13 displays the standardized structural parameter estimates (β) and the theoretical structural model. SEM results indicate a significant direct effect of malleable technology and malleable data on sales-stack perceptions (β = -0.264, p = 0.006; β = .677, p = 0.011) respectively. Effects suggest that malleable technology negatively effects perceptions while malleable data positively effects perceptions, thus supporting hypothesis 1 and 2. Additionally, hypotheses 3 is supported as sales-stack perceptions has a significant and positive path estimate with selling effort (β = .477, p = 0.008), outcome (β = .354, p = 0.010) and behavioral performance (β = .476, p = 0.009).

Indirect Effects. Moreover, the proposed theoretical model suggests that sales-stack perceptions act as a mediator between malleable inputs and sales outcomes. Table 14 displays all indirect effect estimates (including from covariates), bias-corrected confidence intervals ($CI_{95\%}$), and p-values derived from 200 bootstrapped samples. Malleable technology displays a negative indirect effect on effort (ie = -0.126 [-0.239, -0.048]), outcome (ie = -0.093 [-0.204, -0.029]) and behavioral performance (ie = -0.126 [-0.236, -0.052]) respectively. Conversely, malleable data displays positive indirect effect on (ie = 0.323 [0.227, 0.437]), outcome (ie = 0.240 [0.138, 0.348]) and behavioral performance (ie = 0.322 [0.214, 0.404]). Thus, the results suggest an at least partial mediation process through sales-stack perceptions. Furthermore, supporting hypothesis 4 and 5.

Table 13. Parameter Estimates for Direct Effects with Standardized Estimates, CIs, and p-value

	Outcomes:															
	Sales-stack perceptions				Effort				Outcome Performance				Behavior Performance			
		CI_{95}				CI_{95}				CI_{95}				CI_{95}		
	β	Lower Limit	Upper Limit	p-value	β	Lower Limit	Upper Limit	p-value	β	Lower Limit	Upper Limit	p-value	β	Lower Limit	Upper Limit	p-value
Predictors:																
Malleable Technology (MT)	**-0.264**	**-0.401**	**-0.120**	**0.006**												
Malleable Data (MD)	**0.677**	**0.569**	**0.806**	**0.011**												
Sales-stack perceptions (SP)					**0.477**	**0.338**	**0.666**	**0.008**	**0.354**	**0.202**	**0.520**	**0.010**	**0.476**	**0.333**	**0.632**	**0.009**
Covariates:																
Sales Experience (Years)	-0.078	-0.194	0.057	0.220	**0.273**	**0.067**	**0.442**	**0.016**	**0.393**	**0.201**	**0.558**	**0.010**	**0.345**	**0.162**	**0.485**	**0.012**
Organizational Tenure (Years)	0.108	-0.003	0.225	0.056	-0.081	-0.203	0.045	0.264	-0.129	-0.257	0.018	0.088	-0.072	-0.233	0.069	0.267
Age	0.018	-0.101	0.118	0.795	-0.072	-0.227	0.091	0.374	-0.161	-0.341	-0.014	0.031	0.004	-0.160	0.196	0.973
Gender (1=Male/0=Female)	0.053	-0.057	0.158	0.361	0.040	-0.079	0.167	0.535	0.133	-0.003	0.265	0.053	0.085	-0.039	0.231	0.171

NOTE: Parameter estimates with absence of zero in the confidence interval (CI $_{95\%}$. i.e. statisically significant at $p < .05$) are bolded for convenience

Table 14. Parameter Estimates for Indirect Effects, CIs, and p-values

	Effort				Outcome Performance				Behavior Performance			
		CI_{95}				CI_{95}				CI_{95}		
	β	Lower Limit	Upper Limit	p-value	β	Lower Limit	Upper Limit	p-value	β	Lower Limit	Upper Limit	p-value
Predictors:												
Malleable Technology (MT)	**-0.126**	**-0.239**	**-0.048**	**0.010**	**-0.093**	**-0.204**	**-0.029**	**0.010**	**-0.126**	**-0.236**	**-0.052**	**0.005**
Malleable Data (MD)	**0.323**	**0.227**	**0.437**	**0.009**	**0.240**	**0.138**	**0.348**	**0.012**	**0.322**	**0.214**	**0.404**	**0.014**
Covariates:												
Sales Experience (Years)	-0.037	-0.111	0.016	0.120	-0.028	-0.097	0.013	0.134	-0.037	-0.111	0.018	0.147
Organizational Tenure (Years)	0.052	-0.001	0.129	0.057	**0.038**	**0.000**	**0.112**	**0.049**	0.051	-0.001	0.131	0.054
Age	0.009	-0.056	0.058	0.775	0.006	-0.037	0.042	0.794	0.009	-0.056	0.058	0.814
Gender (1=Male/0=Female)	0.025	-0.021	0.084	0.311	0.019	-0.015	0.071	0.134	0.025	-0.021	0.082	0.255

NOTE: Parameter estimates with absence of zero in the confidence interval (CI $_{95\%}$. i.e. statisically significant at $p < .05$) are bolded for convenience

Measurement invariance results

As an initial step in deploying multiple group SEM in a test for moderation, a check for measurement invariance across groups was undertaken. The establishment of metric invariance allows valid comparisons of relationships between groups (Babin, Borges, and James, 2016). The theoretical development above proposes moderation of the structural theories across high and low sales technology adopters. Following the standardized procedures for cross-validation across multiple groups, results must first address whether the same factor structure can represent each group (Hair et al. 2010). Fulfilling the requirements of measurement invariance and structural invariance can provide the grounds for statistical difference between the two groups

Metric invariance. Metric invariance is a necessary condition for allowing valid comparisons of structural relationships between groups. Any hypotheses of moderation in a between group setting depends on the presence of measurement invariance. The test involves examining how much fit from the totally free model is diminished by adding constraints that force each latent variable to be equal across groups. The totally free (meaning the model is unconstrainted between groups – the same structure is deployed but parameters are free to take on unique values in each group) multigroup model indicates moderate fit for a model of this complexity with large numbers of measured variables and a sample size of 280: χ^2 =3008.65, df = 1692, CFI = .83; RMSEA = .059. Next, additional constraints were imposed that forced all loading estimates (Λ_x, Λ_y) to be equal (invariant) between groups. If those constraints hurt fit, the evidence suggests a lack of measurement invariance. Initial measurement invariance test yielded a $^{\Delta}\chi^2$ = 44.32, df = 32 (p =.072) between the totally free (unconstrained) model and the measurement invariance model. These results in table 15 indicate that the equality constraints do not significantly diminish the presence of metric invariance supporting a valid between group comparison. Thus, measurement invariance is suggested and relationships can be compared between groups.

Table 15. Multiple Group Result Fit Indices

Multiple-group Constraints:	χ^2	df	CFI	RMSEA	$\Delta\chi^2$	df	p-value
Totally Free Multigroup Model	3008.65	1692	0.833	0.059	-	-	-
Measurement Invariance	3052.97	1724	0.832	0.059	44.32	32	0.072
Structural Coefficient Invariance	3364.71	1737	0.794	0.065	311.74	13	0.000

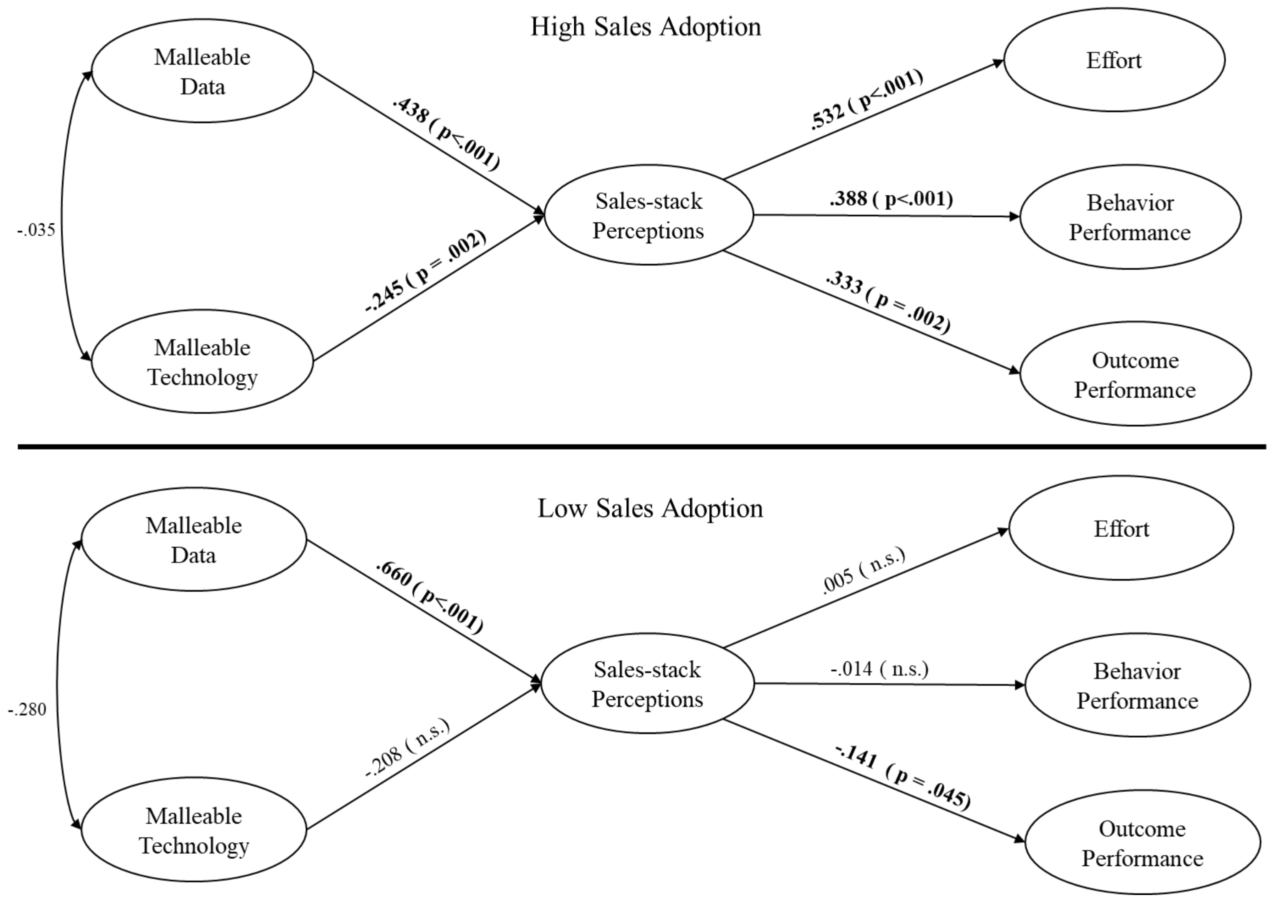
Table 16. 1 DF Moderation Results

Relationship	$\Delta\chi^2$	p-value	note
Malleable technology - Sales-stack perceptions	332.60	<.000	High SA negative effect; Low SA n.s.
Malleable Data - Sales-stack perceptions	333.97	<.000	Low SA larger effect
Sales-stack perceptions - Effort	342.96	<.000	High SA positive effect; Low SA n.s.
Sales-stack perceptions - Behavioral Performance	340.05	<.000	High SA positive effect; Low SA n.s.
Sales-stack perceptions - Outcome Performance	345.85	<.000	High SA positive effect; Low SA negative effect

Structural invariance. The next model includes constraints representing the structural theory proposed. Specifically, placing equality constraints on parameter estimates for the endogenous and exogenous constructs respectively. After enforcing these constraints, the model yielded χ^2 =3364.7, df = 1737, CFI = .794; RMSEA = .065. Not only is both CFI and RMSEA not as good as in the totally free structure model, but the χ^2 difference statistic of 311.74 with 13 degrees of freedom is statistically significant (p<.001). The fact the fit worsens significantly with the addition of structural invariance constraints gives support for moderation by the grouping variable – in this case sales technology adoption.

Figure 7 displays the structural parameters for each group. To test the individual hypotheses that the interaction between malleability and sales technology adoption has an effect on sales-stack perceptions (H6 & H7) and sales outcome (H8); a more detailed examination of the source of moderation is examined. Each structural parameter estimate was constrained, one at a time, to be equal between groups and comparing the fit indices to the totally free structural models. All five paths yield a significant 1 degree of freedom X^2 difference test. Table 16 displays these results. Three of the relationships that are most responsible for the moderation are *sales-stack perceptions – effort, sales-stack perceptions – behavior performance* and *malleable technology – sales-stack perception.* The high sales adopter group, yields a positive effect of perceptions - effort ($\beta = .532$, $p < .001$) and behavior performance ($\beta = .388$, $p < .001$) and a negative effect of malleable technology – perceptions ($\beta = -.245$, $p = .002$). In contrast, in all three paths for the low adopter groups, these relationships yielded statistically insignificant results. Additionally, the *sales-stack perceptions – outcome performance* path is particularly interesting in that the high sales adopter group as a positive effect ($\beta = .333$, $p = .002$), while the low sales adopters have a negative effect ($\beta = -.141$, $p = .045$) respectively. The combined results give support to hypotheses 5, 6 and 7.

Figure 7. Structural Parameter Coefficients Between Groups



V. DISCUSSION

Theoretical Implications

Indigenous theory of sales-stack

The following research tracks the seven-step road map laid out by Hunt (2020) in developing indigenous theory. The research focuses on steps 1 thru 6. Step 7, revising premises is set for future research as research area grows. The underlying concern with the current trajectory of sales technology literature is that it is weighted towards a single use technology. While many past findings help develop the landscape of sales technology research. In order to maintain a relevant bridge between scholarly and managerial research it is imperative to update how scholars view sales technology. It is necessary when conducting research moving forward, those researchers either precisely specify what technology that they are utilizing in their stimuli or look at it from a wholistic approach. Pragmatically, sales technology can be seen more and more being sold as a total system setup (i.e., salesforce, SAP etc.). This calls for scholarly research to follow suit in researching sales technology as a wholistic approach (i.e., sales-stacks).

Prior research has touched on the idea of wholistic sales-technology (Hunter 2019; Hunter & Perreault 2007), but the majority of research focusing on this approach uses it as antecedent but not a focal area of research (Huber 1991, Zablah et al., 2012). The development of the sales-stack indigenous theory allows for researchers to have a collective base when researching wholistic technology. Indigenous theory foundational premises provides an agenda to examine how sales-stacks (wholistic sales technology) impact a salesforce and organization. Similar to S-D logic (Vargo and Lusch 2008), these premises are not concrete but allow for confines to be developed as the research area develops. Sale-stacks six foundational premises promote a loose agenda in order to develop such confines and should be continually scrutinized in order to maintain the relevance. The current research introduces the term sales-stack, provides six foundational premises, develops a valid measure and begins to test some of the confides providing the bedrock for future research in sales-stacks.

Connectivity, the first premise of sales-stacks, is the key attribute that disseminates a sales-stack from single technology. This attribute allows for researchers to focus on how sales technology connects with other technologies within the organization. This also disseminates sales-stacks from sales automation (Buttle et al. 2006; Gronroos 2000). Sales automation focuses on how technology can automate the salespersons processes. On the other hand, sales-stack connectivity focuses strictly on how the technologies cohesively work together to streamline the technological needs of the organization. To this point, no research in the sales literature, has looked at how systems communicate dissemination information from one system to the others.

The second foundational premise (FP2) builds on sales-stacks connective property. That is for an effective sales-stack to be developed the technologies must be idiosyncratic and compatible. Since sales-stacks key differentiation from single use technology is that it contains a portfolio of technologies, it is necessary that each piece of technology that makes up the stack is compatible. Theories like Innovation Diffusion Theory (Rogers 1983, Moore and Benbasat 1991) and Technology Acceptance Model (Davis 1985, 1989) focus on how the salesperson benefits from the adoption of the new technology. However, in few cases, such theories account for the technology fitting into the current organization’s technological infrastructure. Sales-stacks add a new dimension beyond current sales technology adoption literature. For new technologies to be adopted, they must not only benefit the salesperson but must coincide with currently implemented technologies. This additional dynamic adds a new layer researchers need to account for when looking at the impact sales technology has on salesperson outcomes.

Foundational premises 3 and 4 concentrates on adoption properties of sales-stacks once the building blocks (FP1 & FP2) are fulfilled. Sales-stacks need to be adopted by the salesforce (FP3), organization, and industry (FP4). Without the buy-in of all parties involved the sales-stack becomes obsolete and in worst case scenarios can turn into what this research coins as *franken-stacks*. Social exchange theory (Lussier and Hall 2018) examines the cost benefit of a salesperson adopting new sales technology and the benefits it provides to their customers. Sales-stacks eclipse this idea that an effective portfolio of technologies will not only benefit customers but the entirety of the employees within the organization and the other technologies already implemented into the organization.

The last two foundational premises depict the idea that proficiency in current sales-technology flattens sales-stack adoption curves (FP5) and sales-stacks continue to be enhanced with new technology (FP6). The two premises work in a cyclical fashion in that as new technology is introduced it is easier to be adopted because salespeople already have a baseline of comfort from working with their current systems. The idea that proficiency of sales-technology (extrapolated out into sales-stacks) aids in salesperson success is new to the sales technology literature. Prior research focuses on how the salesperson and technology interact to make a salesperson successful. Sales-stacks encompass this idea that the cohesion between the salesperson and technology already exists. The high majority of salespeople depend on technology to do their job. By using sales-stacks instead of a single technology researchers reduce the variability between technologies. That is, if a salesperson already knows how to use one system in their organization, they have a higher baseline of learning an additional technology added to the sales-stack than they would if they had never seen the system before. This baseline knowledge variance has been unaccounted for in prior research causing exaggerated results. Using sales-stacks allows future research to account for proficiency that was only captured by proxies, such as, organizational tenure or sales experience.

Sales-stack effectiveness scale

The development of sales-stacks six foundational premises provides a springboard for sale-technology research to move towards a more pragmatic focus. Building on the foundational premises the *perceptions of sales-stack effectiveness* scale provide the next step in Hunt (2020) framework for developing indigenous theory. Specifically, steps 5 (review foundational premises) and step 6 (test foundations).

In alignment with the sales-stack foundational premises an incremental item pool was developed to encompass current scales that look at single use technology while also taking into account practical salesperson perceptions. After numerous iterations of both component and factor analysis (Hair et al. 2018) the three factors that presented themselves are connectivity, support and hinderance.

The first factor, connectivity, solidifies the main property that differentiates sales-stacks from sales technology. The connectivity factor plays an instrumental role in solidifying the first foundational premise of sales-stacks. Connectivity aids in the dissemination of information throughout an organization and combats *franken-stacks* that salespeople refuse to use. Not only does the connectivity property help explain how salespeople use their sales-stacks, but it also provides a framework to explain how data analytics (Peesker et al. 2022) flow through an organization.

Support allows researchers to determine whether the sales-stack is helping the salesperson in their responsibilities. Sales adoption decisions tend to be made from place of authority, with the intention that it will help the salesperson. However, that is not always the case since the one making the decision is not always the one using the technology (Singh, Flaherty, Sohi, Deeter-Schmelz, Habel, Meunier-FitzHugh, Malshe, Mullins, and Onyemah 2019). With the ability to measure support researchers can begin to look at whether sales adoption decisions are good for the salesforce and not just for organizational outcomes.

Hinderance provides a measure of contrasting ability for sales-stacks. No technology is without flaws. By adding a construct that detects *franken-stacks* researchers now have a tool to determine how poorly implemented sales-stacks can impact the performance of a salesforce or organization. This removes the need to manipulate a stimulus to test ineffective technologies and instead look at them in a more relevant real-world study. Additionally, no sales-stack is perfect and needs to be continually developed and updated (FP6). The hinderance construct accommodates the variance of underperforming systems within a sales-stacks.

The lastly the *sales-stack perception scale* has been validated in both a first order and second order model. Prior researcher (Bagozzi and Heatherton 1994) has shown how the same latent measures can make a psychometrically sound first or second order measure. The flexibility of the scale to be used in a first or second order format, provides an adaptive measure to pursue research questions in an attribute specific or wholistic sales-stack approach. This ability gives researchers a greater depth and breadth when designing studies moving forward.

Sales-stack model

Implementing the sales-stack perceptions scale into a full structural equation model adds another layer of validity for both the scale development and indigenous theory. Result of sales-stack perceptions on behavior performance, outcome performance and salesperson effort provide evidence of nomological validity for the scale. This effect, along with other structural paths, plays a dual role in beginning to look at confines within the sales-stack theory (step 6 in Hunts framework). Specifically, foundational premise 4 was tested through the multi-group analysis between high and low adopters. The results reveal that in high adopters, sales-stack perceptions lead to increased sales outcomes, which is not the case the low sales adopters. This supports the notion of FP4 that the *"value of sales-stacks is created by intra-organizational adoption."*

The model also provides support that the sales-stack perceptions scale is psychometrically sound when used in a second order measure. Results suggest that this scale can be a dependent variable predicted by malleable data and malleable technology, as well as, a statistically significant mediator. The path analysis and multigroup analysis maintain good fit measures for a model of this size, giving more evidence that the scale is a reliable measure (Hair et al. 2018).

Outside of evaluating the measures, the path analysis provides particularly interesting results. Specifically, malleable technology has a negative effect on sales-stack perceptions. This supports the notion that a *franken-stack* is made up of a large amount of single use technologies that will slow down a salesperson. Additionally, malleable data has a positive effect on sales-stack perceptions suggesting that in the digital age when data is at an abundance, salespeople need a cohesive sales-stack to help organize all the data. These effects hold through the mediation of sales-stack perceptions, suggesting that salespeople wholistically understand the tools they need to be successful.

Managerial Implications

While the concept of sales-stacks is not novel to a technologically advance salesforce and in even most cases a salesforce in general the findings within the path analysis provide strong pragmatic direction for sales managers and decision makers.

First and foremost, this study shows that the perceptions of sales-stacks can predict performance outcomes in an organization. This means that sales managers must do a good job of internally selling the sales-stack to the salesforce. If the salesforce has a positive perception of the sales-stack they are more likely to have better behavior performance, outcome performance and effort. Furthermore, malleable technology should be kept to a minimum when developing sales-stacks. The more one-off technologies that go into building a sales-stack, the less likely the salesforce is going to perceive it as effective. Managers can do this by ensuring that they don't over invest in technologies that they don't need or invest in dual purpose technologies cutting down on the number of systems the salesforce uses.

Next malleable data increase the perceptions of sales-stacks. That is, the more data a salesperson has access to the higher the perceptions towards the sales-stack. This goes to show that salespeople see the use for sales-stacks that help them organize customer insight and territory management. In fact, the potential investment in the data leads to higher sales-stack perceptions which entail leads to better sales outcomes and effort. The combination of the two antecedent effects suggest that managers should focus on having a limited amounts of technological systems while having high amounts of data for the salesperson to use.

The multi-group analysis provides the most impactful implications for managers. In particular the research finds that in low sales-stack adopters their perceptions don't impact effort or behavior performance and negatively impact outcome performance. This is the opposite in the high adopter's group where sales-stack perceptions positively impact effort, behavior performance and outcome performance. This suggests that sales managers need to make sure that their salesforce adopts the sales-stack to ensure positive sales outcomes. Furthermore, when recruiting for new sales positions, organizations should inquire about technological acceptance in prior work experience. This could be a good indicator of whether the new sales hire will utilize the sales-stack and how successful they will be in their new roll.

Interestingly, the relationship between malleable technology and sales-stack perceptions has a negative effect in the high sales adoption group but no effect in the low sales adoption group. Additionally, in both groups they have a positive malleable data – sales-stack perception effect, however the lower adoption group has a larger effect. This leads to suggest that low sales adopters might be more stubborn or stuck in their ways. That is, in the low sales adopters know they won't use the sales-stack so it doesn't matter how much technology managers make available. In contrast when they have mass amounts of data low adopters see the value of the sale-stack more because they can't use the data without a system to interpret it for them. Mangers should focus on the data salesforces can utilize to try and persuade the perceptions of the sales-stack and potentially increase adoption.

Table 17. Key Theoretical and Managerial Contributions

Theoretical	Managerial
Proposes theory of sales-stacks ✓ Identifies six foundational premises that make up sales- stacks ✓ Connectivity (FP1) differentiates ST from sales-stacks ✓ Technologies need to integrate with current technologies (FP2) is a new way to look at technology adoption ✓ Creates a foundation for future research on how technology (sales-stacks) impacts a firm and customers (FP3 & FP4) ✓ Creates a foundation for future research on salesperson adoption with machine learning and AI (FP5 & FP6)	*Perceptions of sales-stacks impact performance* ✓ Sales-stacks effectiveness needs to be "sold" to the salesforce to maintain high perceptions ✓ Suggestions from salesforce about improvement to a sales-stack should be taken seriously ✓ Sales-stacks should be leveraged as a competitive advantage when recruiting ✓ Effective sales-stack will increase selling effort. Taking the strain off salesforce.
Develops perceptions of sales-stack effectiveness scale ✓ Validates a three-factor scale through 9 stages of scale development. ✓ Identifies connectivity, support and hinderance as predictors of sales-stack effectiveness. ✓ Supports foundational premises. Connectivity (FP1 &FP2), Support (FP3, FP4, FP5), Hinderance (FP6) ✓ Validates the scale to work both a higher and lower order fashion. Giving flexibility in future research.	*Malleable inputs effect sales-stack perceptions* ✓ Malleable technologies lower perceptions of sales-stacks. Malleable technologies should be kept to only the necessities the stack doesn't provide ✓ Large amounts of data will increase the perceptions of sales-stacks. Firms should not shy away big data mining.
Implements scale in a full structural model ✓ Provides nomological validity to the sales-stack perceptions scale ✓ Supports the notion that sales-stacks lead to positive sales performance ✓ Sales-stack perceptions mediates malleable inputs and sales performance ✓ Sales adoption moderates' malleable inputs on sales-stacks and sales-stack on sales outcomes. Supports FP4.	*Adoption of sales-stacks impacts sales performance* ✓ Salesforce should be strongly encouraged to use the organizations sales-stack. ✓ Salesforce who doesn't adopt the sales-stack tend to be lower performers than their coworkers who do

VI. LIMITATIONS AND FUTURE RESEARCH

This research is subject to a number of limitations. First while measures were taken to ensure that the foundational premises are grounded in, the dissemination of prior theories and practitioner interviews from a broad range of salespeople, there are always gaps of technologies that go unaccounted for. Future research should look to test, validate and restructure the foundational premises as sales-stack technology advances. Hunt (2020) makes a point that step seven of the indigenous theory process is to revise these premises within future publications.

The second limitation of the study is that the confirmatory factor analysis and path models are derived from a single panel of salespeople. The sample size of 280 is not small for confirmatory factor analysis, however, it does the limit the statistical power in the structural model. Future research should look to produce a duplicate study to ensure consistent results within the scale and the path analysis. Additional studies should also consider comparing different groups within the sales-stack perception model. B2B vs B2C, cross-cultural, cross-industry, cross-departmental would all have very different and interesting dynamics on how perceptions of sales-stack differ.

The third limitation is that all measures were used in a self-report capacity. Prior research shows that subjective measures can equate to objective measures (Evanschitzky, Eisend, Calantone and Jiang 2012; Wall, Michie, Patterson, Wood, Sheehan, Clegg and West 2004; Dawes 1999). However, given the potential availability of salesforce objective outcome variables, future studies should look to partner with a firm to ensure the results duplicate when using objective sales measures as opposed the subjective ones used in this study. This would also cut down on the number of latent measures needed to build the model, thus helping in the fit of the structural equation model.

The findings raise several questions for future research. For example, when looking at sales-stack perceptions this research doesn't account for proficiencies in sales-stacks that the respondents already possess. Salespeople who were forced to learn certain technologies at a prior job could carry over the proficiencies to their new role. This could lead them to be a high adopter since they are already comfortable working with the system. Future research should at the minimum control for prior technological proficiencies that might explain the variance between high and low adopters.

Different path models should also be examined when looking at the effects of sales-stack perceptions on outcomes. In the current research direct paths from sales-stack perceptions were utilized to simplify the nomological validity and predictive outcomes of the scale. Future research should focus on grounding the dependent variables in a stronger theoretical approach, such that effort and behavioral performance leads to outcome performance. Furthermore, the malleable antecedents have a potential to impact sales performance. A comparative model between malleable inputs vs sales-stacks would be an interesting dynamic that could solidify the argument that sales-stack perceptions increase performance.

Lastly, the longitudinal propositions should be examined. From a theoretical perspective it would be expected that sales outcomes play a major impact on sales-stack perceptions. Due to time constraints in collecting the data the current study would not allow for a longitudinal collection. The research has provided foundational premises of sales-stack, a valid psychometric measure, and an initial SEM model to guide the future theoretical and empirical development of sales-stack.

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APPENDIX

Appendix 1. Structural Equation Model Measures

Sales-stack perceptions (HOC) - *Study 2 (Galvan et al.)*
Sales-stack perceptions (LOC) -*Support*
My organization's portfolio of technologies effectively supports my selling activities.
I get more work done because of my organization's portfolio of technologies.
I make smarter decisions because of my organization's portfolio of technologies.
I feel more confident in my decisions because of my organization's portfolio of technologies.
My organization's portfolio of technologies allows me to stay extremely organized at the task in hand.
Sales-stack perceptions (LOC) -*Connectivity*
My organization's portfolio of technologies is all connected to each other.
My organization's portfolio of technologies communicates seamlessly with one another.
My organization's portfolio of technologies connects with each other to act as one.
The information needed to do my job flows seamlessly between all technologies within my organization.
The sales technologies I use interact perfectly with one another.
Sales-stack perceptions (LOC) -*Hinderance*
I waste a lot of time working around the bugs in my organization's technology.
Using my organization's portfolio of technologies gets in the way of my job effectiveness.
Customers sometimes get annoyed by issues caused because my organization's technologies are inefficient.
I believe my organization's sales force feels hindered by my organization's technologies that do not work together.
Malleable Data (HOC) - *(Peesker et al. 2022)*
Malleable Data (LOC)- *Analytics and territory management data*
My organization has funnel data to accurately forecast results.
My organization has funnel data to understand variance to quota.
My organization has data to monitor potential customer churn.
My organization has funnel data to adjust sales effort
Malleable Data (LOC)- *Customer Insight data*
My organization has data to customize selling approach.
My organization has data to identify high-potential vs. low-potential customers.
My organization has data to understand industry sectors.
My organization has data to identify customer pain points.
Malleable technology (HOC) -*(Hunter and Perreault 2007)*
Compared to other competitors my organizations use of sales technology to…
Malleable technology (LOC) - *Access*
Routine - Sporadic
Frequent - infrequent
A major emphasis - not a major emphasis
Hesitant - confident
Malleable technology (LOC) - *Analyze*
Routine - Sporadic
Frequent - infrequent

A major emphasis - not a major emphasis
Hesitant - confident
Malleable technology (LOC) - *Communicate*
Routine - Sporadic
Frequent - infrequent
A major emphasis - not a major emphasis
Hesitant - confident
Selling Effort -*(Brown and Peterson 1994)*
Compared to average salesperson in your organization…
The number of hours I put into my sales role each week is:
The amount of time I spend communicating with my customers each week:
My overall selling effort each week:
Behavioral Performance -*(Behrman and Perreault 1982)*
I am very effective in maintaining good customer relations.
I am very effective in providing accurate information to customers and other people in my company.
I am very effective in acquiring the necessary knowledge about my products, competitor's products and my customer's needs.
Outcome performance - *(Behrman and Perreault 1982)*
I am very effective in contributing to my firm's market share.
I am very effective in generating a high level of dollar sales.
I am very effective in selling to major accounts.
I am very effective in exceeding annual sales targets and objectives.
Sales Technology Adoption -*(Davis Bagozzi and Warshaw 1989)*
I consider myself a frequent user of my company's sales-stack tools.
I fully use the capabilities of our sales-stack programs.
I have completely integrated our sales-stack into my sales process.
I use our sales-stack only for the tasks that are required by our company.
I utilize different sales-stack in an integrated way so that they work well together.

Appendix 2. First Order Scale Item Measurement Properties

	Support (Sup)	Connectivity (Con)	Hinderance (Hin)	Pipeline Mangement (PM)	Customer Insight (CI)	Access (Acc)	Analyze (Alz)	Communicate (Comm)	Effort (Eff)	Behavior Performance (BP)	Outcome Performance (OP)
Sup1	0.91										
Sup2	0.90										
Sup3	0.91										
Sup4	0.91										
Sup5	0.90										
Con1		0.88									
Con2		0.93									
Con3		0.88									
Con4		0.89									
Con5		0.87									
Hin1			0.89								
Hin2			0.78								
Hin3			0.76								
Hin4			0.80								
PM1				0.87							
PM2				0.86							
PM3				0.85							
PM4				0.89							
CI1					0.80						
CI2					0.77						
CI3					0.72						
CI4					0.82						
Acc1						-0.81					
Acc2						-0.90					
Acc3						-0.83					
Acc4						0.70					
Alz1							-0.88				
Alz2							-0.96				
Alz3							-0.89				
Alz4							0.72				
Comm1								-0.93			
Comm2								-0.96			
Comm3								-0.87			
Comm4								0.67			
Eff1									0.58		
Eff2									0.80		
Eff3									0.89		
BP1										0.73	
BP2										0.75	
BP3										0.78	
OP1											0.75
OP2											0.86
OP3											0.83
OP4											0.82
AVE	81.8%	79.1%	65.3%	75.1%	66.8%	66.3%	74.8%	74.7%	58.7%	56.6%	66.8%
CR	0.96	0.95	0.88	0.92	0.86	0.89	0.92	0.92	0.81	0.80	0.89

Appendix 3. Original Pool of Scale Items

The sales tools I use, communicate with one another
The sales tools I use, interact with one another
The information needed to do my job seamlessly flows from each system
I trust the information coming from my organizations sales systems
To my knowledge the information in my organizations system is correct
I believe the information in my organizations sales system is accurate
I use the information from my organizations sales stack to present to clients
The technology in my organization’s sales stack is shared with my client
I use the technology in my sales stack because most of the industry uses it
Most of our industry uses similar technology in their sales stack as my organization
I believe my organization has a competitive advantage based on the sales stack they have acquired
I am more efficient in my work because of my organization’s sales stack
My organizations sales stack allows me to do more work in less time
My organizations sales stack allows me to be more efficient in completing my sales responsibilities
I primarily use my organizations sales stack to prospect for clients
I primarily use my organizations sales stack to communicate clients
I primarily use my organizations sales stack to sell to clients
I couldn’t complete my responsibilities without using my organizations sales stack
I primarily use my organizations sales stack to gather insights about the market
I primarily use my organizations sales stack to maintain my strategic partnership with my clients
I primarily use my organizations sales stack to organize my client base
I primarily use my organizations sales stack to organize projects with the organization
I primarily use my organizations sales stack to support other programs within the organization
My organizations sales stack automates systems that would not normally communicate with each other
My organizations sales stack connects all systems within the organization
My organizations sales stack is primarily used for internal processes
My organizations sales stack is primarily used for external processes
My organizations sales stack supports me with both internal and external operations
I am confident in my organization’s sales stack
I self-sufficiently use my organizations sales stack
My organizations sales stack is similar to what I have used in passed companies
My organizations sales stack is intuitive to use
I required little training to use my organizations sales stack
There is nothing I would change to my organization’s sales stack
I am required to use my organizations sales stack to do my job
I could do my job more easily without using my organizations sales stack
My organizations sales stack interface is easy to use
I make smarter decisions because of my organization’s sales stack
I feel more confident in my decisions because of my organization’s sales stack
My organizations sales stack seems more advanced than our competitors
I consider my organizations sales stack a competitive advantage
I get more work done because of my organization’s sales stack
I have never second-guessed data coming out of my organization’s sales stack
The sales stack my organization uses was recommended to us by our customer
My organizations synchronously work with our customers systems
My organizations sales stack is an example of the industry best
My organizations sales stack allows me to work faster
My organizations sales stack allows me to stay organized at the task in hand
It would be difficult to do my job without the support of my organization’s sales stack
I never second guess my organizations sales stack
The majority of my day is spent using my organizations sales stack
My organizations sales stack allows for upper management to track my progress
I feel forced to use my organizations sales stack
I would not use my organizations sales stack if it was not required

I believe there are better technologies within the industry to support my organizations sales stack
My organizations sales stack communicates with all systems within the organization
My organizations systems are all connected to each other
My organizations sales stack provides all the technologies I need to do my job well
My organizations sales stack is easy to use
My organizations sales stack requires little to no training
My organizations sales stack is revered in the industry
My organizations sales stack allows for me to be more effective at my job
My organizations sales stack automates my workload for me
We can do more with fewer people because of the effectiveness of our sales stack.
I waste a lot of time working around the bugs in our sales stack
I've lost clients because of the ineffectiveness of our sales stack.
I've lost leads because of the sales stack.
I could prospect better without having to rely on all this technology
Our sales stack is more a set of separate tools than an integrated system.
Customers are sometimes inconvenienced because of difficulties with the sales stack.
Assuming I have access to the system, I intend to use it
Given that I have access to the system, I predict that I would use it.
Using the system improves my performance in my job.
Using the system in my job increases my productivity
Using the system enhances my effectiveness in my job.
I find the system to be useful in my job.
My interaction with the system is clear and understandable.
Interacting with the system does not require a lot of my mental effort.
I find the system to be easy to use.
I find it easy to get the system to do what I want it to do.
My companies sales stack helps me plan selling activities
My organizations sales stack aids me in receiving information from a team member
My organizations sales stack aids me in receiving information from a manager
My organizations sales stack aids me in receiving information from headquarters
My organizations sales stack aids me obtaining work-related information from non-company data bases
My organizations sales stack aids me in providing information to team members
My organizations sales stack aids me in providing information to my managers
My organizations sales stack aids me in providing information to headquarters
My organizations sales stack aids me in producing notices of, or invitations to, meetings or activities
My organizations sales stack aids me in providing information to customers
My organizations sales stack aids me in participating in sales meetings
My organizations sales stack aids me in planning work related travel activities
My organizations sales stack aids me in recording and retrieving customers contact information
My organizations sales stack aids me in identifying potential new customers
My organizations sales stack aids me in preparing sales presentations
My organizations sales stack aids me in learning about existing products
My organizations sales stack aids me in learning about new products
My organizations sales stack aids me in learning about competitive products
My organizations sales stack aids me training and educating customers
Entering data wastes time that I could spend serving client needs
My organization's technology gives me the creeps
Parts of our sales stack restrict my freedom
The lack of integration of our sales technology interferes with my ability to delivery outstanding customer experiences.
Our web site sucks.
Using the technology like the company wants mean constant interruptions that keep me from pursuing more business
Our sales stack reduces my ability to deliver the human touch to customers.
The sales stack makes decisions for me that take away my power to be 100% effective
The sales stack is like big brother, I feel like I always am being watched

Most of the sales staff feels hindered by technologies that do not always work together
I'm sometimes uncertain as to what technology to employ to be effective
I can maintain better data about customers than can the sales stack
Customers sometimes get annoyed by issues caused because our technologies are inefficient

VITAE

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North Central College
Master of International Business Administration *May 2015*

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Bachelor of Science in Marketing *May 2013*

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INTERNATIONAL, NATIONAL, & REGIONAL CONFERENCE PRESENTATIONS

Swab, R.G., **Galvan, J. M**., & Sherlock, C. (2021). *The Interaction of Trait Competitiveness and Core-Self-evaluations on Predicting Competitive Attitudes*. Eastern Academy of Management Annual Meeting. [Conference Abstract]

Galvan, J. M. (2019). *Amending online service failures through virtual front-line employees.* Society for Marketing Advances Conference. November 7, New Orleans, LA. [Conference Presentation Abstract] 628-629.

Galvan, J.**M**, & Vitell, S. J. (2019). *An Exploratory Factor Analysis: Towards a Digital Consumer Ethics Scale.* Southeast Marketing Symposium Conference. February 8, Memphis, TN. [Conference Presentation Abstract] 48.

Galvan, J.M., & Shaner, M. B. (2018). *What They Don't Know Won't Hurt Them: How White Label Products Influence Consumer Reviews.* Society for Marketing Advances Conference. November 3, West Palm Beach, FL [Conference Presentation Abstract] 539-540.

JOURNAL SUBMISSIONS UNDER REVIEW

Swab, R.G., Sherlock, C., & **Galvan, J.M.** *Mechanisms Through Which Core Self-Evaluations Predict Competitiveness.* Journal: *Psychological Reports* Status:1st round submission.

SELECTED MANUSCRIPTS IN PREPARATION FOR JOURNAL SUBMISSION

Locander, D.A., Babin, B.J., & **Galvan, J.M.** *Creative Selling Leverages Better Performance? Salesperson Intuition, Emotional Intelligence, and Deliberation Avoidance.* Journal: Industrial Marketing Management

Galvan, J.M., Babin, B. J., & Boles, J. S. *Typology of Sales Technology: defining organizational sales-stacks, developing foundational premises and directing future research.* Target: *AMS Review*

Shaner, M. B., **Galvan, J.M.**, & Hunter, G. *Boundary Spanners: The Role of Salespeople in the New Product Development Process.* Target: *Journal of the Academy of Marketing Science.*

Thomas, A.M., **Galvan, J.M.**, & Morgan, A. *In 280 Characters or Less: The Impact of Celebrity Tweets on Shareholder Wealth.* Target: *Journal of Marketing*

Galvan, J.M., & Vitell, S. J. *An Exploratory Factor Analysis: Towards a Digital Consumer Ethics Scale*. Target: *Journal of Business Ethics*

Galvan, J.M., *Amending online service failures through virtual front-line employees.* Target: *Journal of Consumer Research*

PROFESSIONAL AFFILIATIONS

American Marketing Association
DOCSIG

SERVICE TO THE PROFESSION

Conference Reviewer, *Society for Marketing Advances Conference* *August 2021*
School of Business AACSB Assurance of Learning Committee, *University of Mississippi*
August 2018 – May 2019
Conference Volunteer, *Society for Marketing Advances Conference* *November 2018*
Conference Reviewer, *Society for Marketing Advances Conference* *July 2018*

TEACHING EXPERIENCE

University of Mississippi (2017 - Present)

Course	*Dates*	*Class Size*	*Average Rating**
Essentials of Marketing *(GB 350)*	Fall 2021	20	TBD
Principles of Marketing *(MKTG 351) – Hybrid*	Summer 2021	15	TBD
Global Marketing and Supply Chain *(MKTG 452 - Online*	Spring 2021	78	4.16
Social and Digital Media Strategy *(MKTG 370) - Online*	Spring 2021	50	4.40
Social and Digital Media Strategy *(MKTG 370) - Hybrid*	Fall 2020	10	4.62
Social and Digital Media Strategy *(MKTG 370) - Hybrid*	Fall 2020	36	4.50
Principles of Marketing *(MKTG 351) - Online*	Summer 2020	33	4.52
Sales Management *(MKTG 458)*	Spring 2020	36	4.70
Global Marketing and Supply Chain *(MKTG 452)*	Spring 2020	70	4.59
Global Marketing and Supply Chain (MKTG 452)	Fall 2019	50	4.39
Introduction to Retailing *(MKTG 361)*	Fall 2019	46	4.59
Retail Strategy *(MKTG 488)*	Summer 2019	16	5

* Overall instructor rating 1 = poor, 5 = excellent

PROFESSIONAL EXPERIENCE

eCommerce Consultant, *Galvan Consulting Group LLC.* *August 2017 – Present*

- Integrate Salsify platform into existing organizational systems

- Create formulas to ensure consistent brand message across retailers
    - API mapping to current supported customers
    - Automate sell sheets and digital catalogs
    - Train cross-functional teams to utilize Salsify in day-to-day activities
- Launch new eCommerce accounts
    - Negotiate selling terms and conditions
    - Manage new customer setup and integration
    - Transition account to sales team upon setup completion
- Operate as interim eCommerce account manager
    - Prior accounts: Amazon seller & vendor central, Wayfair, Houzz, Walmart.com, Zulily, BedBathBeyond.com & many more

Account Manager eCommerce, *World Kitchen LLC* *March 2016 – August 2017*

- Increased YoY top line sales: YTD Zulily (+**415%**) Wayfair (+**53%**), Amazon (+**15%**)
- Lead Go-To- Market new product launch campaigns across six key brands
    - **165** new product launches
    - Report monthly ROI post launch
- Created annual multimillion-dollar A&P budget
- Developed 3PL partnership with Castlegate fulfillment
- Collaborated with cross functional teams on new product development
- Analyze weekly POS and develop demand forecast

Sales Coordinator, *World Kitchen LLC* *March 2015- March 2016*

- Implemented Pyrex 100 Omni channel marketing campaign
    - Generated **+250M** impressions, 100 days of Pyrex Media tour, World record unveiling
- Managed all digital content and new product setups through Salsify
    - Created and oversaw enhanced digital copy including Amazon A+, Vine, AMG, AMS
- Work with outside agency partners on marketing copy, and digital assets
- Lead new vendor setup's working cross functionally with all internal business units

Customer Marketing Intern, *World Kitchen LLC* *October 2014- March 2015*

- Supported the Brand and Sales Management team cross functionally
    - Utilize BW, SAP, Business Intelligence
- Enhanced and updated sell sheets, sell stories and support material
- Verified pricing to ensure the correct margins are reached