Journal of Business Research 102 (2019) 163–177

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

The role of lead management systems in inside sales performance

Alhassan Ohiomah[a,*], Pavel Andreev[a], Morad Benyoucef[a], David Hood[b]

[a] Telfer School of Management, University of Ottawa, Ottawa, ON K1N 6N5, Canada
[b] VanillaSoft, Gatineau, QC J8Y 3Y7, Canada

A R T I C L E I N F O

Keywords:
Inside sales
Lead management system
PLS-SEM
Sales performance

A B S T R A C T

Understanding how the use of IT influences the performance of inside sales is imperative, yet there is a lack of research in this area. This study empirically validates a conceptual model based on the Technology-Task-Fit theory, capturing the impact of lead management systems (LMS) on inside sales performance through the following mediators: task characteristics (call quantity and lead follow-up intensity), selling behavior (adaptive selling), and salesperson characteristics (technical and salesmanship skills). Using PLS-SEM on 108 responses collected from sales professionals, our analysis shows that the use of LMS in inside sales affects performance via improving salespeople's adaptive selling and lead follow-up intensity, technical and salesmanship skills; together these variables explain over a half (55%) of the variance of sales performance. Our findings aim to inform academics and practitioners on the key enablers of inside sales performance and IT usage approaches that can optimize marketing output in the inside sales industry.

1. Introduction

Advances in information technology (IT) have been the catalyst for significant changes in sales operations (Rapp, Agnihotri, & Forbes, 2008; Rutherford, Marshall, & Park, 2014). The reaction to these changes has forced most organizations to restructure their sales functions through a rapid increase in the utilization of inside sales (Gessner & Scott Jr, 2009; Järvinen & Taiminen, 2016). Inside sales refer to a sales method that uses one or more IT tools to execute routine sales tasks remotely (i.e., over the phone, e-mail, the Web, and other Internet-based technologies) without the traditional face-to-face interaction with customers (Seley & Holloway, 2008).

Pursuing leads (i.e., potential customers) until qualification and/or conversion to sale is a fundamental function of inside sales (Pullins, Timonen, Kaski, & Holopainen, 2017). Resources are spent on marketing to generate these leads through advertising, web campaigns and trade shows, but most of the leads are ignored and never contacted by salespeople (D'Haen, Van den Poel, & Thorleuchter, 2013; VanillaSoft, 2014) because of poor work conduct among salespeople (Monat, 2011; Sabnis, Chatterjee, Grewal, & Lilien, 2013), and/or improper lead management systems (D'Haen, Van den Poel, Thorleuchter, & Benoit, 2016; Smith, Gopalakrishna, & Chatterjee, 2006; VanillaSoft, 2014). It is safe to say that marketing efforts in lead generation are worthless if leads are not properly managed. Yet, the literature lacks studies that suggest effective lead management practices can improve inside sales performance. The literature presently has two major limitations.

First, there is currently a shortage of research studies on inside sales in general. Particularly, little is known about factors that improve lead management outcomes in inside sales (Ohiomah, Benyoucef, & Andreev, 2016). It was suggested that factors that improve the performance of outside sales may not necessarily do the same for inside sales because of the differences in sales interactions, selling tasks, environment, and organizational contexts (Chapman, 2018; Rutherford et al., 2014; Singh & Koshy, 2010). Yet, existing studies have mostly focused on identifying factors that improve the lead management outcomes of outside sales (Rutherford et al., 2014) while often ignoring inside sales (Harmon & Funk, 2014).

Second, little has been done to investigate sales-technology approaches to the inside sales process that can help shape future development decisions and enhance sales performance (Kuruzovich, 2013; Ohiomah et al., 2016; Rutherford et al., 2014). Prevailing studies on the role of IT in sales have focused primarily on outside sales (Ahearne, Jones, Rapp, & Mathieu, 2008; Ferrell, Gonzalez-Padron, & Ferrell, 2010; Honeycutt Jr., 2005). Inside sales are fundamentally metrics, process, and technology-driven, and they rely on innovative IT tools to engage and develop relationships with prospects and customers (Seley & Holloway, 2008). It should be noted that many inside sales programs have failed to reach their objectives because of the shortfalls of poor

* Corresponding author.
E-mail addresses: aohio100@uOttawa.ca (A. Ohiomah), andreev@Telfer.uOttawa.ca (P. Andreev), benyoucef@Telfer.uOttawa.ca (M. Benyoucef), david@vanillasoft.com (D. Hood).

https://doi.org/10.1016/j.jbusres.2019.05.018
Received 11 May 2018; Received in revised form 14 May 2019; Accepted 15 May 2019
Available online 31 May 2019
0148-2963/

Customer Relationship Management (CRM) systems or related IT tools that support inside sales activities (Marketo, 2008). Still, to the best of our knowledge, no study has empirically investigated the effect of lead management systems on inside sales performance. Lead management systems (LMSs) are IT tools designed to automate and support effective lead management. They are the most deployed technology by inside sales organizations (Ostrow, 2009), and as a result, they represent an important investment (Maddox, 2013). Without effective LMSs, leads generated through marketing campaigns can hurt downstream sales outcomes because of wasted effort on poorly qualified leads and/or delays and inefficiencies in following up with leads (Smith et al., 2006). Currently, LMSs can be classified into List-based and Queue-based LMSs. A **list-based** LMS provides a salesperson with a long list of leads and it is upon the salesperson to filter and select which leads to manage. Lead selection in these systems relies heavily on the salesperson's individual decision-making capability. When a salesperson is done with a lead, he/she goes back to the list to find the next best lead to contact based on his/her qualification criteria. A **queue-based** LMS uses predefined business rules and a configured workflow sequence to automatically filter and provide a salesperson with the next-best lead to manage. When a salesperson is done with a lead and enters the result of the call into the system, the system automatically selects the next best lead to be contacted by the salesperson. Here, decisions on who manages what leads are taken by the LMS based on predefined business rules set by the organization. Knowing which lead to contact, how and when to contact the lead represents a significant challenge for inside salespeople. Such knowledge directly impacts the performance of inside sales, yet existing literature falls short of this needed knowledge.

We address these gaps in the literature by answering the following question: "*What is the role of LMS use on key drivers and enablers of inside sales performance?*" We aim to understand the impact of employing both LMS types (List-based and Queue-based) and how both approaches influence key enablers of inside sales performance. Accordingly, our research objectives are (1) to introduce and empirically validate a conceptual model that captures how LMS use influences key factors of inside sales performance; (2) to investigate the difference between how List-based and Queue-based systems influence inside sales performance; and (3) to provide LMS adopters with recommendations regarding LMS use in order to improve inside sales performance. We argue that the problems encountered by inside sales organizations with regard to lead management can be addressed by highly efficient LMSs. The systems and procedures used to manage leads are key determinants for sales success. Therefore, organizations need comprehensive LMSs that are built on best practices.

This study makes three main contributions. First, we introduced a conceptual model based on the Technology-to-Performance Chain (TPC) of the Task-Technology-Fit (TTF) theory by Goodhue and Thompson (1995). Second, after developing and administering an online survey, we employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess the model. Third, we identified the theoretical and practical implications of our findings, namely, that *"lead management systems affect inside sales performance via improving salespeople's adaptive selling, lead follow-up intensity, technical skills and salesmanship skills, and together these variables explain more than half (55%) of the variance of inside sales performance"*.

This paper is organized as follows. Section 2 presents the theoretical background and formulation of our conceptual model. The research design, data collection and analysis method are detailed in Section 3. In Section 4, we provide an evaluation of our conceptual model using PLS-SEM guidelines. Finally, in Section 5, we discuss the findings of our research and detail key theoretical contributions, practical implications, limitations, and future research opportunities.

2. Theoretical background

This paper extends a conceptual model previously introduced in Ohiomah et al. (2016). The conceptual model was proposed but was not empirically validated. The model was developed through a synthesis of the literature and was centered on the Technology-to-Performance Chain (TPC) of the Task-Technology-Fit (TTF) theory by Goodhue and Thompson (1995). The TTF-TPC theory argues that individuals' use of IT influences their performance and that the benefits will be higher only if IT is properly utilized and fits the requirements of the task it supports (Goodhue & Thompson, 1995). This theory helps in understanding the link between LMS use and inside sales performance through the completion of the lead management task. Furthermore, this theory is not only concerned with technology, task, and individual characteristics but also accommodates the assessment of individual attitudes and behaviors.

Previous studies investigating sales performance have espoused the TTF-TPC theory (e.g., Ahearne et al., 2008; Hunter & Perreault Jr, 2006; Román & Rodríguez, 2015) but their focus was on outside sales. We argue that the literature can benefit from a technology-to-performance chain model for inside sales, particularly to provide insights on how technology (i.e., LMSs) use can support lead management activities and drive inside sales performance. Moreover, recent studies argue that the mediating role of key selling factors in the association between technology use and performance remains unexplored (Román & Rodríguez, 2015). Hence, we propose a model classifying the impact of LMS use on inside sales performance through the following mediators: (1) *Task characteristics* (i.e., activities performed by individuals to achieve outputs (Goodhue & Thompson, 1995); (2) Selling behavior (i.e., what salespeople do during the execution of selling-related activities to aid the performance of their jobs); and (3) Salesperson's characteristics (i.e., a combination of a salesperson's selling-related knowledge, skills, attitude, role perception and motivation portrayed during selling).

2.1. Conceptual model

The conceptual model (Fig. 1) suggests that LMS use indirectly influences inside sales performance through the following mediating variables: *task characteristics* (i.e., call quantity and lead follow-up intensity); *selling behavior* (i.e., adaptive selling); and *salesperson characteristics* (i.e., technical skills and salesmanship skills). Consistent with Barker's (1999) perspective that salespeople should be evaluated based on output and behaviors that they can control, our conceptualization of sales performance refers to *the degree of efficiency and effectiveness to which a salesperson achieves the objectives of lead management for an inside sales organization* (Ohiomah et al., 2016).

2.1.1. Mediating variables-to-sales performance

2.1.1.1. Call quantity. Call quantity refers to the number of sales calls made by salespeople to contact a lead through the phone or Internet technologies with the intention of selling a product or service. Call productivity (i.e., number of calls over hours worked) is said to increase performance in Ahearne, Hughes, and Schillewaert (2007). However, the use of *hours worked* can be a misleading when assessing call productivity of salespeople because it also includes the time salespeople spend on non-selling activities (e.g., territory management). Accordingly, scholars have advised against the use of hours worked to measure sales input activities (Rapp et al., 2008). Ahearne et al. (2008) found that call activity (i.e., number of calls) had a positive and significant relationship with performance. Furthermore, the number of sales calls has served as a key measure of a salesperson's efficiency (Zallocco, Pullins, & Mallin, 2009) and hard work (Rapp, Ahearne, Mathieu, & Schillewaert, 2006). Thus, we posit that.

H1. Call quantity positively affects sales performance.

2.1.1.2. Lead follow-up intensity. Following up on leads during pre-sale and post-sale is an essential part of salespeople's job design (Pullins et al., 2017). Lead follow-up intensity is the degree to which a

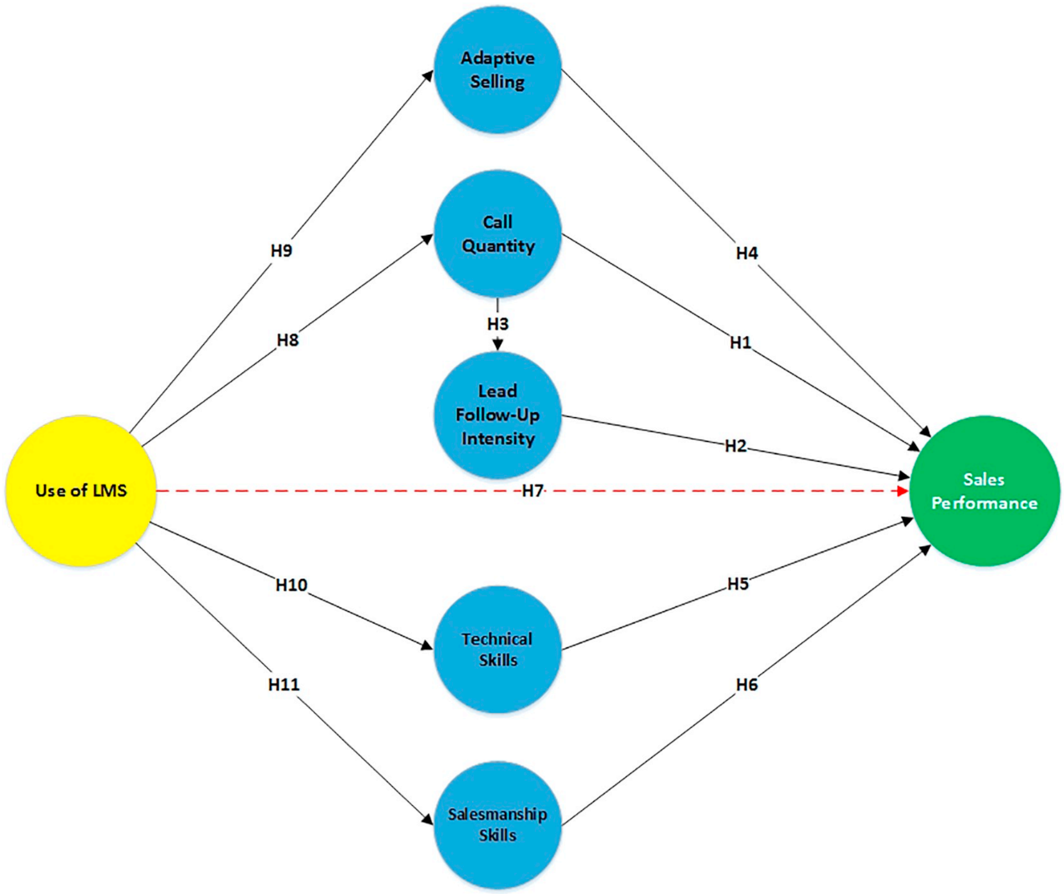

Fig. 1. Conceptual model.

salesperson closely pursues leads and maintains contact with them until the close of a sale or until a lead is abandoned (Sabnis et al., 2013). Within inside sales practice, persistency, consistency and speed to contact are key factors in salespeople's lead follow-up endeavors and are seen by practitioners as significant sales performance indicators (Elkington & Oldroyd, 2016; Sabnis et al., 2013; Smith et al., 2006). Smith et al., (2006) suggested that leads contacted immediately (i.e., within the first 5 days of being identified) have a 20% better chance of making a purchase than those contacted afterwards. Sabnis et al., (2013) found that salespeople perform better when they increase their lead response and follow-up activities. Therefore, we argue that.

H2. Lead follow-up intensity positively affects sales performance.

There are several channels used by salespeople to contact leads, including phone, email, SMS, and social media (e.g., Twitter and LinkedIn), in order to nurture leads and take them from being aware of a product/service until they make a purchase decision. In order to follow up on leads, salespeople must make calls. Hence call quantity is an essential component of the lead follow-up process in inside sales. An increase in the number of a salesperson's calls will increase his/her contact ratio via a shorter sales cycle (i.e., from first contact attempt to close of sale) (Ohiomah et al., 2018). Bradford, Johnston, and Bellenger (2016) found that increased effort (i.e., the average number of sales calls per week) reduced sales cycle time, and ultimately improved lead conversion outcomes. Furthermore, every attempt to connect with a lead improves contact persistency and consistency, interaction duration, and overall follow-up intensity (Moutot & Bascoul, 2008; Smith 2006). Hence, we argue that.

H3. Call quantity positively affects lead follow-up intensity.

2.1.1.3. Adaptive selling. Adaptive selling means modifying *"selling behaviors during a customer interaction or across customer interactions based on perceived information about the nature of the selling situation"* (Weitz, Sujan, & Sujan, 1986, p. 175). The successful implementation of adaptive selling requires that a salesperson senses customers' personalities, moods, information needs, risk aversion, etc., and then modifies selling strategies to match the needs of customers (Porter, Wiener, & Frankwick, 2003). The last 20 years have produced empirical evidence to support the hypothesis that high performing salespeople are able to adapt to different selling situations (Ahearne et al., 2008; Boorom, Goolsby, & Ramsey, 1998; Franke & Park, 2006; Goad & Jaramillo, 2014; Jaramillo & Grisaffe, 2009; Kadic-Maglajlic, Vida, Obadia, & Plank, 2016; Porter et al., 2003; Román & Iacobucci, 2010). More so, some scholars (e.g., Giacobbe, Jackson Jr., Crosby, & Bridges, 2006; Verbeke, Dietz, & Verwaal, 2011) rank adaptive selling as an important driver of sales performance. However, other studies (e.g., Keillor, Parker, & Pettijohn, 2000) found non-significant relationships between the practice of adaptive selling and improved sales performance. Limbu, Jayachandran, Babin, and Peterson (2016) for instance found that adaptive selling increased relationship quality with customers but does not improve salesperson outcome performance. This highlights inconsistencies in the relationship between adaptive selling and sales performance. Hence, there is a need for further investigation to clarify conflicting results from earlier studies (Ahearne et al., 2008; Itani, Agnihotri, & Dingus, 2017). Accordingly, we propose the following hypothesis:

H4. Adaptive selling behavior positively affects sales performance.

2.1.1.4. Selling skills. Salespeople require certain basic skills for performing the necessary tasks for the sales job (Singh & Venugopal, 2015). Rentz, Shepherd, Tashchian, Dabholkar, and Ladd (2002) proposed a scale that integrates three skill-based dimensions: (1) interpersonal skills (e.g., verbal and nonverbal communication proficiency); (2) salesmanship skills (e.g., prospecting and qualifying customers, and sales presentation); and (3) technical skills (e.g., selling knowledge). Since then, other studies (e.g., Singh & Venugopal, 2015; Wachner, Plouffe, & Grégoire, 2009a) have adapted Rentz et al.'s (2002) dimensions in their investigation of salespeople's skills. Nevertheless, in this study, we only investigate technical and salesmanship skills. We do not investigate interpersonal skills because they reflect aspects like nonverbal expressions, empathy, awareness of nonverbal communication, ability to control and regulate nonverbal displays of emotions, etc. (Rentz et al., 2002), which cannot be effectively measured within the context of our study.

2.1.1.5. Technical skills. Rentz et al. (2002) described technical skills as a salesperson's knowledge of the market, product features and benefits, salesperson's own company procedures, and competitors' products and services and sales policies. This knowledge is critical to a salesperson's performance (Baldauf & Cravens, 2002; Carter, Henderson, Arroniz, & Palmatier, 2014; Groza, Locander, & Howlett, 2016; Miao & Evans, 2012a). Knowledgeable salespeople are familiar with their product or service, have an understanding of customer needs and expectations, and learn critical information about their customers (Rapp et al., 2006). Within sales management research, technical skills have been labelled with different terms, including selling knowledge, selling-related knowledge (Miao & Evans, 2012b; Verbeke et al., 2011), knowledge breath (Carter et al., 2014), industrial and organizational knowledge (Groza et al., 2016) and understanding customers (Rodriguez, Ajjan, & Peterson, 2014). Verbeke et al., (2011) found selling-related knowledge to be the most important driver of sales performance. Miao and Evans (2012a) found a positive relationship between selling knowledge and sales performance. Groza et al. (2016) found a positive relationship between organizational knowledge and sales performance. Furthermore, Plouffe, Hulland, and Wachner (2009) found that the impact of technical skills on sales performance was inconsistent based on different data sets and different measures of sales performance (i.e., subjective vs objective). Plouffe et al. (2009) suggested that technical skills were not significant when sales performance was measured using objective reports (i.e., supervisory report of salesperson performance). Accordingly, in the context of inside sales it is important that we verify the consistency of the significance of technical skills in explaining sales performance. Hence, we posit that.

H5. A salesperson's technical skills positively affect sales performance.

2.1.1.6. Salesmanship skills. Salesmanship skills include prospecting for new customers, qualifying customers by uncovering and understanding their needs, customizing solutions for each lead, presenting solutions back to customers, handling customer objections and questions regarding the proposed solution, and closing the sale (Rentz et al., 2002). A salesperson with strong prospecting and qualification abilities can identify and categorize different client types, as well as their associated product and selling requirements (Román & Iacobucci, 2010). Proper identification of leads, particularly those with high purchase intent can increase the likelihood of conversion to sales (Ahearne et al., 2007; Román & Rodríguez, 2015). More importantly, salespeople who know how to effectively present information about the products they sell can provide the right product and service to the right lead, address concerns while interacting with a lead, increase a lead's perception of trust and satisfaction, and ultimately increase sales performance (Abdolvand & Farzaneh, 2013; Johlke, 2006). Finally, Wachner, Plouffe, and Grégoire (2009b) suggested a positive effect of salesmanship skills on sales performance. Accordingly, we posit that.

H6. A salesperson's salesmanship skills positively affect sales performance.

2.1.2. The use of LMS-to-mediating variables

Technology plays an ever-increasing role in sales (Ahearne, Srinivasan, & Weinstein, 2004). Technology does not only enhance the quality and speed of information gathering (Speier & Venkatesh, 2002) but also automates the sales process and enables salespeople to better analyze and interpret data about their leads, competition, and market (Ahearne, Mathieu, & Rapp, 2005). LMSs collect, unify, and organize data and information about leads to make the lead management process more efficient and effective. Low usage of implemented technology is a major factor underlying low productivity and returns on organizational IT investments (Venkatesh & Davis, 2000). Accordingly, our study focuses on the effective use of LMSs. The ***use of LMSs*** here *refers to the degree to which salespeople integrate the full potential of LMSs to carry out lead management tasks*. The effective use and frequency of use of technology drive a salesperson's performance (Burton-Jones & Grange, 2012; Sundaram, Schwarz, Jones, & Chin, 2007). The above discussion shows that the impact of LMS use on sales performance is not direct but is rather mediated through effective integration and utilization of LMSs during the execution of key lead management activities. Accordingly, we posit that.

H7. The use of LMSs does not directly influence sales performance.

In general, the literature provides evidence that the use of sales technologies (i.e., SFA and CRM) improves a salesperson's call quantity (Ahearne et al., 2007; Ahearne, Jelinek, & Rapp, 2005; Rapp et al., 2006). This argument can be used when discussing the impact of the use of LMSs on call quantity because SFA and CRM are similar technologies that offer functionalities (e.g., call history logs) that are used to manage leads. The use of LMSs can allow salespeople to make more sales calls. Indeed, technology automates the selling process and increases the capacity of salespeople to make more sales calls (Ahearne et al., 2007; Rivers & Dart, 1999). Technology usage increases the proportion of successful sales calls by reducing the amount of time salespeople spend on non-selling tasks (Moutot & Bascoul, 2008). Sales technologies used for lead management can also schedule and automatically route leads to a salesperson to contact, which can enable a salesperson to contact a large number of leads efficiently (Kuruzovich, 2013). Accordingly, we posit that.

H8. The use of LMSs increases salespeople's call quantity.

Salespeople can only tailor a sales presentation to the unique needs and concerns of their leads if they have the right information about the leads, competitors and market (Ahearne et al., 2008; Itani et al., 2017; Park, Kim, Dubinsky, & Lee, 2010). Correspondingly, a key role of LMSs is to allow salespeople to collect information about leads, identify and understand their needs and engage adaptively with customers and prospects (Ahearne et al., 2008; Park et al., 2010). Accordingly, we posit that.

H9. The use of LMSs increases salespeople's adaptive selling behavior.

The importance of a salesperson's use of information in modern day selling cannot be over emphasized. Salespeople need extensive access to data and information to be successful, and the fundamental purpose of information technology is to provide users with access to data and information (Hunter & Perreault Jr, 2006). The impact of technology on technical skills has been confirmed in the literature. Ahearne et al. (2008) found that salespeople who effectively use technology will possess relevant knowledge of the sales situation. Hunter and Perreault Jr. (2007) found that using sales technology for accessing information was positively associated with administrative performance. Moreover, Hunter and Perreault Jr. (2007) found that using sales technology for analyzing and better understanding information about the market, customer and product can help build better relationships with customers.

LMS use can provide salespeople with access to massive amounts data, help them synthesize such data, and identify patterns within it. These patterns can represent usable knowledge and market intelligence. This can allow salespeople to learn more about their customers and use the information to stay informed and knowledgeable before, during and after customer interactions, which may help foster better business relationships and ultimately improve sales performance. Accordingly, we posit that.

H10. The use of LMSs increases salespeople's technical skills.

IT supports salespeople with the information needed to target the best leads at the best time. The enhanced visibility gained through the repository of information needed for contact and account management should motivate salespeople to properly select sales calls and only work on those they can justify, which should improve sales ratios. Ahearne et al. (2007) showed that the use of technology will enhance salespeople's ability to target and qualify leads through effective analysis of lead information. Román and Rodríguez (2015) found that technology usage has a direct influence on qualification skills, a construct related to salesmanship skills.

LMS use improves access to data about customers, which is important for organizational CRM endeavors (Anderson, 2007; Park et al., 2010). LMSs can help salespeople identify and select leads with high interest, potential and ability to buy, and provide tools to manage contact (e.g., calendars for setting appointments, customized sales presentations, document generation etc.) with these leads. LMSs can offer sophisticated features such as call scripting to support calls, as well as features to maintain organizational charts, customer notes, and supplemental sales information during customer interactions. To summarize, using information available through an LMS about leads, market and competitors, salespeople can effectively complete their lead management task through better content delivery, quick access to information, quality interactions and better prospecting through strategic lead sorting and classification (Ahearne et al., 2007; Park et al., 2010). Accordingly, we posit that.

H11. The use of LMSs increases salespeople's salesmanship skills.

3. Research method

We developed an online survey to operationalize our conceptual model. Most of the measurement items used in the survey were adapted from previous research that has explored similar constructs. A preliminary survey was conducted with a sample of 6 expert respondents from diverse inside sales industries to examine the items as well as the reliability and face validity of their scales. All 6 experts are members of the American association of inside sales professionals (https://www.aa-isp.org/) and thus, we assume they are credible. All 6 expert respondents gave positive feedback and confirmed that they understood all items, that all items were applicable to their industry and that the available scales were adequate. In the end, twenty-three (23) items were retained, and they all represented their target constructs (see Table 1). The feedback from experts confirms the reliability and consistency of our measurement items.

3.1. Data collection

The original sample population consisted of nearly a thousand sales professionals from several inside sales organizations using either list-based or queue-based LMSs. Using random sampling, our final sample consisted of 483 selected contacts of sales managers, supervisors, and top-level executives of these inside sales organizations. For that, we selected at least one contact from each organization in the population. A web link to our survey was disseminated through an email invitation to these contacts to gather information on each organization's assessment and perceptions of the impact of its LMS usage.

To minimize response bias, we collected data in two (2) rounds. First, we selected 300 potential participants and sent emails inviting them to participate in the survey. Having recognized that follow-ups can effectively increase the response rate (Van der Stede, Young, & Chen, 2005), a follow-up email reminder was sent out to these potential participants after one week. One month later, we selected the remaining 183 potential participants and sent them an invitation email to participate in the survey. After a week, we followed up with an email reminder to the second group. The survey was conducted in January–February 2015 and lasted 6 weeks.

Most participants were recruited from companies in North America, and few in Australia, New Zealand, the United Kingdom and Brazil. At the close of the survey, we collected a total of 122 responses (25.3% response rate). Given that respondents were under no obligation to complete the entire survey, 14 responses were incomplete, leaving us with 108 valid responses.

3.2. Data analysis

To test our hypotheses, we implemented Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 3.2.7. PLS-SEM is a component-based approach used to analyze hypothesized relationships in a path model (Urbach & Ahlemann, 2010). We chose PLS-SEM over other covariance-based SEM (CB-SEM) approaches because it allows us to simultaneously investigate both measurement and structural models. Another reason for choosing PLS-SEM is that it accommodates the small sample size of this study, and it can process together the different measurement scales of this study (Urbach & Ahlemann, 2010; Wold, 1985). In addition, it allows for the use of both reflective and formative measurement indicators in our model. Note that the PLS approach is recognized as highly appropriate at the earlier stages of a model's development, which is the case in this study.

After carrying out a listwise deletion of responses with missing data, we retained 108 complete responses, which is sufficient to validate our model. The rule of thumb is that the minimum sample size should exceed 10 times the largest number of formative indicators used to measure a particular construct, or 10 times the largest number of paths directed to a construct in the model (Hair Jr, Hult, Ringle, & Sarstedt, 2016). The construct with the most connected paths in our model is Sales Performance, which has six (6) paths. This means that a minimum sample size of sixty (60) is required to validate our research model. Furthermore, according to Hair Jr. et al., (2016)'s suggestion regarding sample size, we would need 66 samples for a statistical power of 80% given R^2 value of at least (0.25) for the sales performance construct (i.e., construct with the largest number of paths) for a 1% probability of error.

4. Results

Table 2 shows the demographic profile as reported by the respondents to our survey. The respondents represent a variety of industries. On the high side, 26.9% and 15.7% of them represent telemarketing, and business and professional services respectively. The majority of our respondents are sales managers and top-level executives. Over 62% of the respondents are from companies that use B2B models. Additionally, 84.3% of the respondents come from small and medium-sized organizations. Finally, the majority (82.4%) of our respondents are users of queue-based systems because they all use an LMS by the same vendor who encourages the use of queue-based systems.

4.1. Model evaluation

We employed a two-stage approach to empirically validate our model. The first stage evaluates the measurement models (Section 4.2) for reliability and validity of constructs and measures, and the second

Table 1
Survey instrument and constructs measurement.

Constructs	Indicators	Measures	Scales	Sources adapted
Use of Lead Management Systems (LMS)	LMSU1	Follow-up on leads	Seven point scale 0 = "They do not use this technology at all", and 6 = "They use this technology to a great extent"	(Rapp et al., 2008)
	LMSU2	Access product information		
	LMSU3	Access information about leads to adapt sales calls and/or presentation based on a lead's specific need		
	LMSU4	Record lead contact information		
Adaptive selling	AS1	My salespeople use a variety of sales approaches	Seven point Likert scale 1 = "Strongly disagree" and 7 = "Strongly agree".	(Robinson, Marshall, Moncrief, & Lassk, 2002)
	AS2	My salespeople like to experiment with different sales approaches		
	AS3	When my salespeople feel that their sales approach is not working, they can easily switch to another sales approach.		
Call quantity	CI1	Please report, on average, how many calls each sales person makes per hour	Numerical scale 0–50	(Ahearne et al., 2007)
Lead follow-up intensity	LFU1	On average, how many follow-up calls do your salespeople make with a lead before closing them out?	Numerical scale 0–20	(Elkington & Oldroyd, 2007; Ohiomah et al., 2018)
	LFU2	Would you agree that your salespeople log every sales call?	Seven point Likert scale 1 = "Strongly disagree" and 7 = "Strongly agree".	
	LFU3	How fast do your salespeople contact a new lead?	Seven point scale 1 = "Very slow" and 7 = "Very fast"	
Technical skills	TS1	My salespeople are an excellent resource of competitive information	Seven point Likert scale 1 = "Strongly disagree" and 7 = "Strongly agree".	(Behrman & Perreault, 1982; Rentz et al., 2002)
	TS2	My salespeople have a lot of information on industry trends		
	TS3	My salespeople know all the specifications and applications of our products		
	TS4	My salespeople are excellent an source of information about their "product category"		
Salesmanship skills	SS1	My salespeople present information clearly and concisely to leads	Seven point Likert scale 1 = "Strongly disagree" and 7 = "Strongly agree".	(Ahearne et al., 2007; Behrman & Perreault Jr., 1982; Rentz et al., 2002)
	SS2	My salespeople identify, understand and address concerns of leads		
	SS3	My salespeople are very good at identifying, selecting and calling on profitable leads		
	SS4	My salespeople consistently call on leads that can provide the most business		
Sales performance	SP1	My salespeople produce high market share for our company		(Behrman & Perreault Jr., 1982)
	SP2	My salespeople sell products with higher profit margins.		
	SP3	My salespeople produce sales with long term profitability		
	SP4	My salespeople exceed all annual sales lead management objectives for our company		

Table 2
Demographic profile of respondents.

Industry representation	Count	%	Position of respondents	Count	%
Telemarketing	29	26.85%	Supervisor/manager	44	40.74%
Business & professional Services	17	15.74%	Top level executive	35	32.41%
Education	9	8.33%	Administrative/support personnel	17	15.74%
Others	9	8.33%	Other	12	11.11%
Media & communications	8	7.41%	Total	108	100%
Technology	7	6.48%			
Insurance	6	5.56%	Company size of respondents	Count	%
Banking & finance	5	4.63%	Small	66	61.11%
Energy	4	3.70%	Medium	25	23.15%
Merchant services	4	3.70%	Large	17	15.74%
Home improvement	3	2.78%	Total	108	100%
Non-profit	3	2.78%			
Health	2	1.85%	Type of LMS Use	Count	%
Manufacturing & product Sales	2	1.85%	Queue-based system	89	82.41%
Total	108	100%	List-based system	19	17.59%
			Total	108	100%
Company size of respondents	Count	%			
Business-to-business (B2B)	67	62.04%			
Business-to-consumer (B2C)	21	19.44%			
Both	20	18.52%			
Total	108	100%			

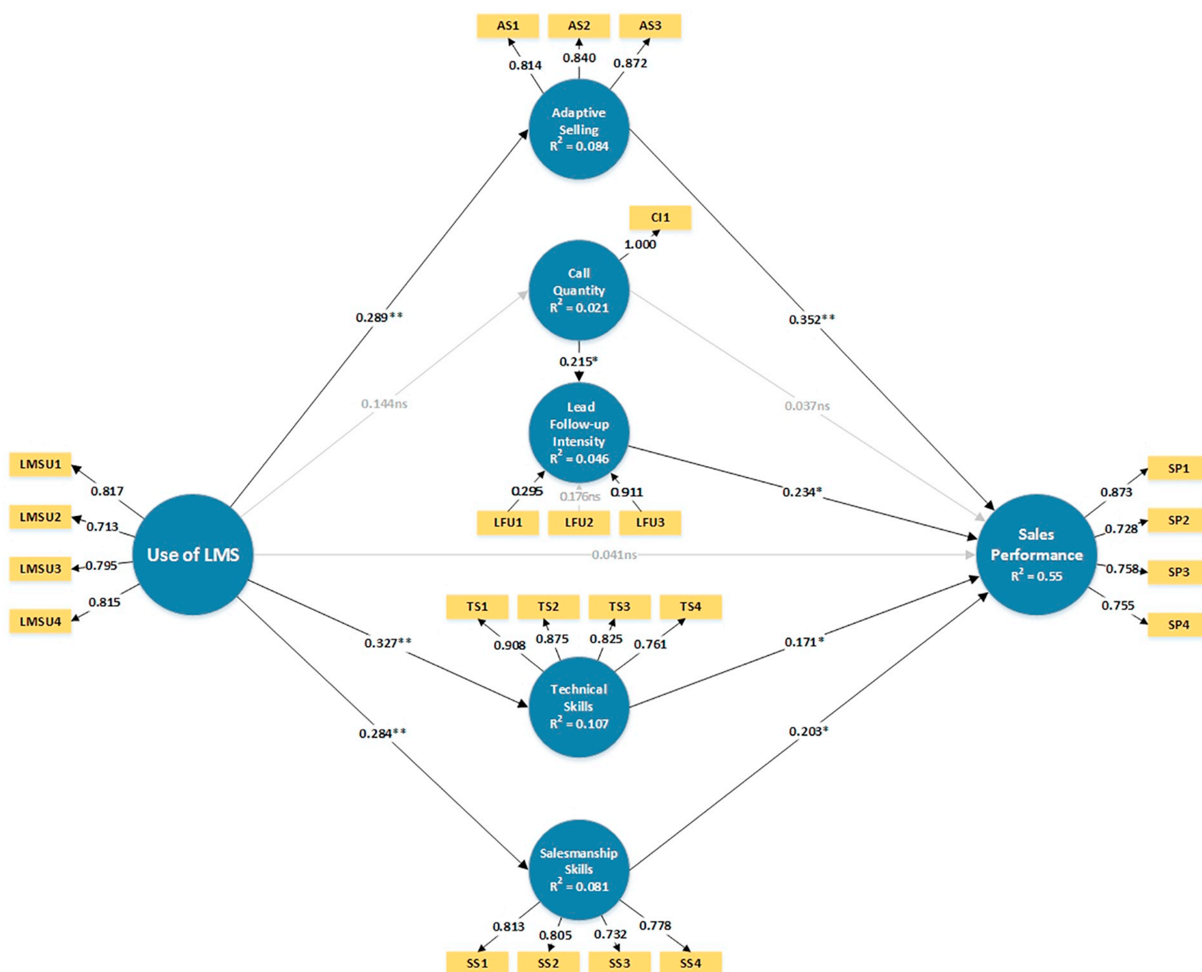

Fig. 2. Evaluation of measurement and structural models of general model.

stage evaluates the structural model (Section 4.3) to assess the relationships between constructs in the path model (Chin, 1998; Hair Jr et al., 2016; Henseler, Ringle, & Sinkovics, 2009) and predictability of the model. In addition, we conducted an individual analysis of just the queue-based dataset of both the measurement and structural models to explore possible changes in the outcome (Section 4.4). Accordingly, we developed two different models: a general model that captures data from all respondents, and a queue-based model that only captures data from respondents using queue-based LMSs. Evaluation of the model for list-based LMSs was not conducted due to the small sample size (see

Section 5.3 for the limitations of the study). Fig. 2 shows the results of our structural and measurement models' evaluation of the general model.

4.2. Evaluation of measurement models

Our study uses both reflective and formative indicators to estimate our constructs. In the reflective case, it is assumed that a latent variable causes the observed items, while in the formative case, the observed items cause a latent variable (Jarvis, MacKenzie, & Podsakoff, 2003). The path model includes five reflective constructs (i.e., *use of LMSs, adaptive selling, call quantity, technical skills, salesmanship skills and sales performance*), and one formative construct (*lead follow-up intensity*).

4.2.1. Evaluation of reflective measurement models

We tested our reflective measurement model for internal consistency reliability, indicator reliability, convergent validity, and discriminant validity (Chin, 1998; Hair Jr et al., 2016; Henseler et al., 2009; Henseler, Ringle, & Sarstedt, 2015). Note that these measures are not appropriate for evaluating call quantity because it is a single item construct with a fixed loading of 1.000.

4.2.1.1. Internal consistency reliability. We used Cronbach's alpha (CA) and Composite reliability (CR) to test for internal consistency reliability. Table 3 shows that all our reflective constructs have internal consistency reliability. Values are above 0.785 and 0.861 for CA and CR, respectively. Both scores are above the recommended 0.7 required levels (Chin, 1998; Cronbach, 1951).

4.2.1.2. Indicator reliability. The reliability of an indicator relies on the inference that a construct should explain at least 50% of each of its associated indicator variance (Chin, 1998). The indicator loadings of our reflective constructs are well above the required 0.7 and are statistically significant (Chin, 1998; Gefen, Straub, & Boudreau, 2000; Henseler et al., 2009). This confirms the reliability of our indicators. Having met the criteria for internal consistency reliability and convergent validity, we chose to retain this indicator (Hair Jr et al., 2016) (see Fig. 2 and Table 3).

4.2.1.3. Convergent validity. The AVE values of our reflective constructs are all above 0.5 (Chin, 1998; Fornell & Larcker, 1981) (all above 0.609), meaning that each construct explains over 50% of their indicator variance (see Table 3).

4.2.1.4. Discriminant validity. We assess the reflective constructs for discriminant validity using the Fornell-Larker criterion, cross loadings and the Heterotrait-monotrait (HTMT) ratio. Table 4 illustrates the result of the Fornell-Larker criterion, indicating that the square root of the AVE of each construct exceeds the correlation with other constructs in the path model, thus signifying that each construct is unique because it shares more variance with its associated indicators than with other constructs in the path model.

The cross loadings test shows that none of the indicators load higher on any construct other than the target one in our path model (see Appendix A). This is consistent with the principle that an indicator should load higher on its target construct than on any other construct in the path model (Chin, 1998).

Furthermore, we used HTMT to assess between-trait correlations and within-trait correlations (i.e., the true correlations between two constructs) (Henseler et al., 2015). To establish discriminant validity, the literature suggests that true correlations between two constructs should be below 0.9 if both constructs are conceptually similar, and 0.85 if both constructs are conceptually different. A correlation close or equal to 1 infers a lack of discriminant validity. Table 5 illustrates that all HTMT correlations between two constructs are < 0.782. Additionally, a bootstrapping procedure reaffirms that true correlations between two constructs are < 1 with a confidence interval of 97.5%, thereby confirming the discriminant validity of our reflective constructs (Hair Jr et al., 2016; Henseler et al., 2015). Tables 4 and 5 as well as Appendix A show the distinctiveness of constructs in our path model.

4.2.2. Evaluation of formative measurement models

We tested our formative measurement model for content validity, indicator weights and significance level, and indicator multicollinearity (Andreev, Heart, Maoz, & Pliskin, 2009; Hair Jr et al., 2016).

4.2.2.1. Content validity. Given the limited theoretical research in this field, we established content validity of our formative construct based on industrial practices. The discussion below establishes content validity for the Lead follow-up intensity formative construct.

Lead follow-up Intensity is the ability of salespeople to closely pursue leads and to maintain contact with those leads until the close of a sale or a lead is abandoned. This construct is shaped by *persistency*, *consistency* and *immediacy* (Elkington & Oldroyd, 2016; Ohiomah et al.,

Table 3
Internal consistency reliability, indicator reliability and convergent validity statistics for general model.

Constructs	Convergent validity	Internal consistency reliability		Indicator reliability			
	AVE	Composite reliability (CR)	Cronbach's Alpha (CA)	Indicators	Indicator loadings	T statistics	*P* values
Use of LMS	0.618	0.866	0.798	LMSU1	0.817	14.926	0.000
				LMSU2	0.713	7.407	0.000
				LMSU3	0.795	12.884	0.000
				LMSU4	0.815	15.081	0.000
Adaptive selling	0.710	0.880	0.795	AS1	0.814	15.792	0.000
				AS2	0.840	23.450	0.000
				AS3	0.872	26.709	0.000
Technical skills	0.713	0.908	0.868	TS1	0.908	38.897	0.000
				TS2	0.875	36.179	0.000
				TS3	0.825	14.484	0.000
				TS4	0.761	11.748	0.000
Salesmanship skills	0.613	0.863	0.791	SS1	0.813	16.811	0.000
				SS2	0.805	16.424	0.000
				SS3	0.732	12.750	0.000
				SS4	0.778	11.092	0.000
Sales performance	0.609	0.861	0.785	SP1	0.873	45.792	0.000
				SP2	0.728	7.819	0.000
				SP3	0.758	11.713	0.000
				SP4	0.755	14.086	0.000

Table 4
Construct cross-correlation statistics: Fornell-Larcker criterion for general model.

Constructs	Adaptive selling	Call quantity	Sales performance	Salesmanship skills	Technical skills	Use of LMS
Adaptive selling	0.842					
Call quantity	0.069	1.000				
Sales performance	0.622	0.099	0.780			
Salesmanship skills	0.528	0.022	0.581	0.783		
Technical skills	0.391	−0.136	0.495	0.568	0.844	
Use of LMS	0.289	0.144	0.277	0.284	0.327	0.786

2016; Smith et al., 2006; VanillaSoft, 2014). *Persistency* refers to how many times salespeople attempt to contact a lead, *consistency* refers to the continuous update of information about leads, and *immediacy* concerns how fast leads are first contacted by salespeople. Collectively, these three dimensions define lead follow-up intensity as conceptualized by the industry. We followed the same defining criteria from Jarvis et al. (2003) to conclude that lead follow-up intensity is a formative construct.

4.2.2.2. Indicator validity and multicollinearity. We used the SmartPLS bootstrapping procedure to obtain indicator weights and t-statistics for evaluating the significance of formative indicators. The weights of all our formative indicators are above 0.1, and they are statistically significant except for LFU2 (consistency). We have empirical justification to retain these indicators (Hair Jr et al., 2016) with the exception of LFU2. However, we chose to retain LFU2 (consistency) because it is an important aspect of lead follow-up intensity, and its removal would change the meaning of the defined construct (Jarvis et al., 2003) (see Table 6).

Subsequently, we obtained Variance Inflation Factor (VIF) scores to assess multicollinearity. The VIF scores range from 1.004 to 1.077 (see Table 6). Since the VIF scores are below the 5 threshold (Hair Jr et al., 2016), we validate the absence of multicollinearity in our formative construct.

Speed (y = 0.911) was found to be a major and significant component of Lead follow up intensity. Consistency (y = 0.176) was found to be a weak and insignificant component of Lead follow up intensity but it was retained in the model.

4.3. Evaluation of the structural model

To validate our structural model, we follow the guidelines of Hair Jr. et al., (2016). We also apply recommendations from other studies (Chin, 1998; Henseler et al., 2009).

4.3.1. Coefficient of determination (R^2)

The results indicate that our predictor variables explain 55% ($R^2 = 0.549$) of sales performance variance. The test criteria here specify that values of 0.75, 0.50 and 0.25 are considered substantial, moderate and weak respectively (Hair Jr et al., 2016). Thus, the explained variance of the sales performance is considered moderate. Additionally, LMS use explains 8.4% of adaptive selling variance, 2.1% of call quantity variance, 10.7% of technical skills variance, and 8.1% of salesmanship skills variance. Call quantity alone explains 4.6% of lead follow-up intensity variance.

4.3.2. Significance of path coefficients

We ran bootstrapping with 5000 resamples to evaluate the significance of hypothesized path relationships in our model using t-statistic values. A relationship is said to be statistically significant in the structural model if the t-statistic value is above 1.96 and 2.57 at 5% and 1% significance level, respectively (Hair Jr et al., 2016). Fig. 3 and Table 7 show the significance of our hypothesized path relationships. Eight positive (H2, H3, H4, H5, H6, H9, H10 and H11) and one insignificant (H7) hypothesized relationships were supported, while two positive hypothesized relationships (H1 and H8) were rejected.

4.3.3. Mediator analysis

We also assessed the significance of mediator constructs in the model. Table 7 shows that Adaptive Selling, Technical Skills and Salesmanship Skills significantly mediate the relationship between the Use of LMS and Sales performance (0.228, $p < 0.01$). Since the direct relationship between the Use of LMS and Sales performance is insignificant (0.041, NS), we conclude according to Hair Jr. et al., (2016) suggestion that Adaptive Selling, Technical Skills and Salesmanship Skills fully mediate the relationship between the Use of LMS and Sales performance. Our analysis also shows that Lead Follow-up Intensity did not mediate the relationship between Call Quantity and Sales Performance (0.05, NS). Also, call quantity did not mediate the relationship between the use of the Use of LMS and Lead Follow-up Intensity (0.031, NS).

In addition to the mediation analysis conducted in SmartPLS, we also implement Nitzl, Roldan, and Cepeda (2016) procedure for mediation analysis. The rule of thumb states that VAF (Variance Accounted Factor) values over 80% justify arguments for full mediation in a model. Table 8 shows that 85% of the total effect is due to the mediated effects in the model. The results also confirm that Adaptive selling, Salesmanship skills and Technical skills are the only significant mediators of the Use of LMS on Sales performance.

4.3.4. Effect Size (f^2)

Multiple PLS estimations were carried out, each time excluding an ascendant construct in our path model to identify the contribution of an independent construct on a dependent construct. According to Cohen (1988), f^2 values of 0.02, 0.15 and 0.35 are considered small, medium and large, respectively. Table 9 shows that adaptive selling has a

Table 5
Heterotrait-monotrait ratio (HTMT) test for general model.

Constructs	Adaptive selling	Call quantity	Sales performance	Salesmanship skills	Technical skills	Use of LMS
Adaptive selling						
Call quantity	0.076					
Sales performance	0.782	0.124				
Salesmanship skills	0.656	0.092	0.723			
Technical skills	0.448	0.155	0.568	0.682		
Use of LMS	0.339	0.157	0.335	0.339	0.377	

Table 6
Indicator validity and multicollinearity of formative constructs for general model.

Constructs	Indicators	Weight	STD	T-statistics	P values	VIF
Lead follow-up intensity	LFU1: Persistency	0.295*	0.150	1.963	0.050	1.004
	LFU2: Consistency	0.176^{ns}	0.198	0.886	0.376	1.077
	LFU3: Speed	0.911**	0.114	7.989	0.000	1.077

Notes: Significant at 1% = **, Significant at 5% = * and Non-significant = ns.

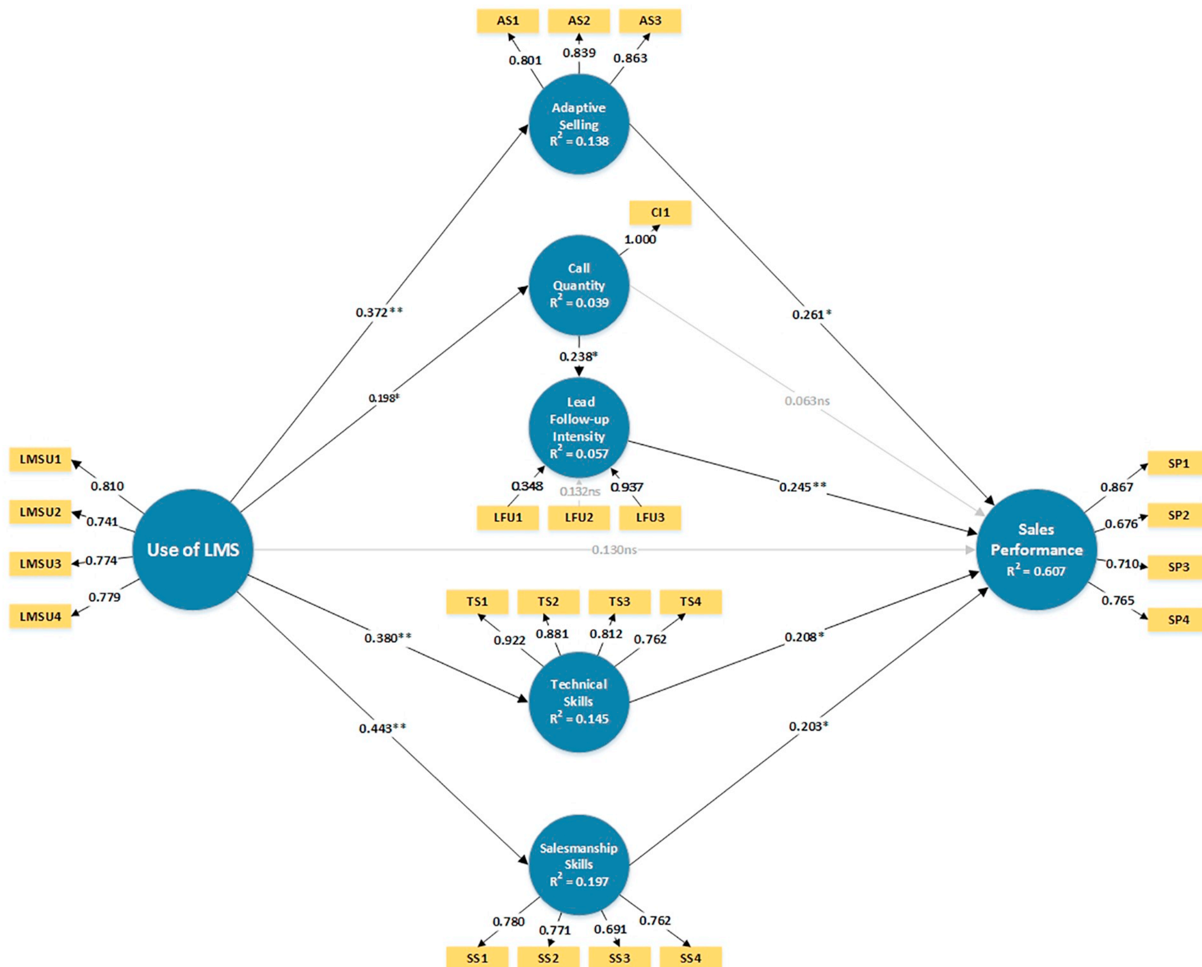

Fig. 3. Evaluation of measurement and structural models of the queue-based model.

Table 7
Significance of path relationships for general and queue-based models.

Hypotheses		General model						Queue-based model					
		Direct effects		Indirect effects		Total effects		Direct effects		Indirect effects		Total effects	
		Path	T-Stat	Path	T-Stat	Path	T-Stat	Path	T-Stat	Path	T-Stat	Path	T-Stat
H1	Call Quantity - > Sales Performance	0.037^{ns}	0.565	0.05 ^{ns}	1.388	0.087^{ns}	1.290	0.063^{ns}	1.035	0.058^{ns}	1.830	0.121^{ns}	1.828
H2	Lead follow-up intensity- > Sales Performance	0.234*	2.272	–	–	0.234*	2.272	0.245**	2.906	–	–	0.245**	2.906
H3	Call Quantity - > Lead follow-up intensity	0.215*	2.141	–	–	0.215*	2.141	0.238*	2.511	–	–	0.238*	2.511
H4	Adaptive selling - > Sales Performance	0.352**	3.357	–	–	0.352**	3.357	0.261*	2.154	–	–	0.261*	2.154
H5	Technical Skills - > Sales Performance	0.171*	2.242	–	–	0.171*	2.242	0.208*	2.194	–	–	0.208*	2.194
H6	Salesmanship Skills - > Sales Performance	0.203*	2.073	–	–	0.203*	2.073	0.203*	2.004	–	–	0.203*	2.004
H7	Use of LMS - > Sales Performance	0.041^{ns}	0.593	0.228**	3.55	0.269**	3.313	0.130^{ns}	1.638	0.290**	4.698	0.421**	5.254
H8	Use of LMS - > Call Quantity	0.144^{ns}	1.646	–	–	0.144^{ns}	1.646	0.198*	2.013	–	–	0.198*	2.013
H9	Use of LMS - > Adaptive selling	0.289**	2.959	–	–	0.289**	2.959	0.372**	3.685	–	–	0.372**	3.685
H10	Use of LMS - > Technical Skills	0.327**	3.611	–	–	0.327**	3.611	0.380**	4.092	–	–	0.380**	4.092
H11	Use of LMS - > Salesmanship skills	0.284**	3.077	–	–	0.284**	3.077	0.443**	5.882	–	–	0.443**	5.882
	Use of LMS - > Lead follow-up intensity	–	–	0.031^{ns}	1.176	0.031^{ns}	1.176	–	–	0.047^{ns}	1.390	0.047^{ns}	1.39

Notes: Significant at 1% = **, Significant at 5% = * and Non-significant = ns.

Table 8
Mediation analysis.

Indirect paths		Original (O)	CI: lower (5%)	CI: upper (95%)	VAF
H9 x H4	LMS- > AS x AS- > SP	0.102**	0.032	0.187	38%
H8 x H1	LMS- > CQ x CQ- > SP	0.005 ns	−0.011	0.025	2%
H11 x H6	LMS- > SS x SS- > SP	0.058*	0.005	0.119	21%
H10 x H5	LMS- > TS x TS- > SP	0.056*	0.013	0.103	21%
H8 x H2 x H3	LMS- > CQ x CQ x LF x LF- > SP	0.007*	−0.001	0.021	3%
Total indirect effect		0.228**	0.038	0.455	85%

Significant at 1% = **, Significant at 5% = * and Non-significant = ns.
Notes: AS: Adaptive selling; CQ: Call Quantity; LF: Lead follow-up intensity; LMS: Use of LMS; SS: Salesmanship skills; TS: Technical Skills.

medium effect on sale performance (f^2 = 0.183), while lead follow-up intensity (f^2 = 0.094), technical skills (f^2 = 0.039), and salesmanship skills (f^2 = 0.050) all have a small effect. Use of LMSs has a small effect of adaptive selling (f^2 = 0.091), technical skills (f^2 = 0.120), and salesmanship skills (f^2 = 0.088). Additionally, call quantity has a small effect on lead follow up.

4.3.5. Predictive relevance (Q^2)

To assess the predictive relevance of our structural model, we ran a Stone and Geisser test using a blindfolding procedure on SmartPLS. A structural model has a predictive relevance if the Q^2 values of all endogenous constructs in a path model are above zero (> 0) (Hair Jr et al., 2016). Table 10 confirms that all endogenous constructs in our path model have predictive relevance as the Q^2 values are all above zero.

4.4. Comparison of data groups

As mentioned earlier, the majority of our respondents reported that they use queue-based LMSs. The small sample of companies using list-based LMSs does not allow for conducting a cross-comparison analysis of queue-based versus list-based LMS users; hence, it is difficult to effectively compare their performance impacts. A viable alternative is to run a cluster analysis of queue-based LMSs and compare the outcome with the whole sample. Ketchen Jr and Shook (1996) described cluster analysis as a statistical technique that sorts responses into similar groups.

We carried out PLS-SEM for only queue-based LMS users (89 respondents out of 108). The evaluation of the measurement models met the reliability and validity criteria for all tests with no significant differences in values. However, a structural model evaluation for just queue-based LMS companies revealed some crucial and statistically significant differences in direct and indirect effect between the constructs (see Table 7), as well as the coefficient determination of endogenous constructs. Fig. 3 shows that one previously non-significant path relationship is now statistically significant. The use of LMSs positively affects call quantity (0.198, $p < 0.05$). Furthermore, the queue-based model explains 60.7% of the sales performance variance. In addition, adaptive selling, technical skills and salesmanship skills explain variances of 13.8%, 14.5%, and 19.7% respectively.

For the effect size (f^2) analysis, we determined that the contribution of each independent construct on the endogenous construct in the model differed considerably from the original analysis. The difference here is that the use of LMSs has a small effect size on call quantity and a medium effect size on adaptive selling, technical skills and salesmanship skills. Additionally, adaptive selling now has a small effect on sales performance.

5. Discussion and implications

This study seeks to contribute to the growing body of technology-to-performance research by presenting an empirical model validating the impact of the use of LMSs on key factors (as mediators) of inside sales performance. To start with, we adopt a model that captures key inside sales performance drivers and enablers, after which we empirically identified the impact of the use of LMSs on these drivers. Most of the concepts used in this study were previously recognized in the literature; however, these concepts have not been used in a single study investigating sales performance. Eleven (11) hypotheses were proposed and our findings provide support for nine (9) of them. Overall, we can state that the use of LMSs affects inside sales performance via improving salespeople's adaptive selling, technical skills and salesmanship skills. Together, these variables explain more than half (55%) of the variance of inside sales performance.

5.1. Theoretical implications

Our reflective review reveals several theoretical contributions, which are explained below.

Contrary to previous research (Ahearne et al., 2007; Zallocco et al., 2009), this study found no correlation between call quantity and sales performance (H1 rejected). Ahearne et al. (2008) suggested that call

Table 9
Effect Size (F^2) statistics for general model.

Hypotheses		General model		Queue-based model	
		F^2	Effect	F^2	Effect
H1	Call Quantity - > Sales Performance	0.003	–	0.008	–
H2	Lead follow-up intensity - > Sales Performance	0.094	Small	0.103	Small
H3	Call Quantity - > Lead follow-up	0.049	Small	0.060	Small
H4	Adaptive selling - > Sales Performance	0.183	Medium	0.106	Small
H5	Technical Skills - > Sales Performance	0.039	Small	0.062	Small
H6	Salesmanship Skills - > Sales Performance	0.050	Small	0.056	Small
H7	Use of LMS - > Sales Performance	0.003	–	0.031	Small
H8	Use of LMS - > Call Quantity	0.021	Small	0.041	Small
H9	Use of LMS - > Adaptive selling	0.091	Small	0.161	Medium
H10	Use of LMS - > Technical Skills	0.120	Small	0.169	Medium
H11	Use of LMS - > Salesmanship skills	0.088	Small	0.245	Medium

Table 10
Blindfolding statistics for predictive relevance (Q2) for general model.

Constructs	General model			Queue-based model		
	SSO	SSE	Q^2 (=1-SSE/SSO)	SSO	SSE	Q^2 (=1-SSE/SSO)
Adaptive selling	324	307.155	0.052	267	245.262	0.081
Call quantity	108	106.671	0.012	89	88.389	0.007
Lead follow-up intensity	324	320.089	0.012	267	266.286	0.003
Salesmanship skills	432	415.794	0.038	356	322.651	0.094
Technical skills	432	404.051	0.065	356	324.394	0.089
Sales performance	432	304.006	0.296	356	250.973	0.295

productivity had a significant impact on sales performance. We treated call quantity with the same measure but found no statistically significant relationship between the two constructs. Call quantity should not be restricted to salespeople making high numbers of calls but making quality calls that could improve lead conversion ratio. In reality, a salesperson can make 10 sales calls in an hour, and only connect to one lead. Another salesperson might make 5 sales calls and successfully connect to 3 leads. Hence, we believe that within the inside sales industry, call quantity should not be about the number of sales calls made, but should consist of factors that increase connect ratio, and ultimately the sale of products and services. We argue that the relationship between call quantity and sales performance may be highly dependent on salespeople contacting the right leads with persistency, consistency and immediacy.

This study provides support for the relationship between lead follow-up intensity and sales performance (H2 supported). This outcome is consistent with the inside sales industry's expectations on lead follow-up undertakings (Elkington & Oldroyd, 2016; VanillaSoft, 2014). This relationship can be justified with the fact that salespeople are more likely to qualify and convert leads to sales if they consistently contact leads with persistency and immediacy (Sabnis et al., 2013; Smith et al., 2006). We also found a positive relationship between call quantity and lead follow-up intensity (H3 supported). Obviously, the number of sales calls made by salespeople is a key indicator of the effort they devote to lead follow-up. The remote nature of inside selling makes sales calls a significantly interactive medium for completing the lead follow-up task.

The impact of adaptive selling behavior on sales performance has been previously tested and validated in the sales literature (Ahearne et al., 2008; Franke & Park, 2006; Goad & Jaramillo, 2014; Kadic-Maglajlic et al., 2016; Verbeke et al., 2011). The result of our research confirms that adaptive selling has a moderate impact on sales performance and is the most significant driver of sales performance in our empirical model (H4 supported). We believe this correlation is substantiated because when salespeople fit their sales approach to meet the specific needs of a lead, they increase the likelihood of closing a sale, while building an effective relationship with the lead. Leads are more likely to buy from salespeople who they believe treat them uniquely and meet their specific needs.

Our study shows that a salesperson's technical and salesmanship skills improve sales performance (H5 and H6 supported). This confirms our prediction that those salespeople who contact leads who provide the most business, demonstrate company products and/or services, handle customer objections and questions, close sales and possess enhanced selling knowledge about their market, customer and products tend to achieve higher performance. Salespeople are key to finding target customers, conveying an organization's message to them, and understanding customer needs and expectations related to the product and/or service. This is an important task that salespeople cannot afford to fail at because a failure will result in loss of sales.

Furthermore, our study assessed the direct relationship between the use of LMSs and sales performance and found no significant correlation between the two variables (H7 supported). However, when we assessed an indirect relationship between the use of LMSs and sales performance (via mediating variables), we found a positive and significant correlation. As predicted, this means that the impact of the use of LMSs on sales performance is experienced through selling tasks, behaviors and characteristics, which drive sales performance. The use of LMSs did not relate significantly to call quantity in the general model (H8 rejected).

The literature suggests that the use of IT directly improves adaptive selling (Ahearne et al., 2008), and our study confirms a direct impact of the use of LMSs on adaptive selling (H9 supported). LMSs provide salespeople with access to information about leads to adapt sales calls and/or presentation based on a lead's specific needs. Also, our findings reveal that LMS use improves a salesperson's technical and salesmanship skills (H10 and H11 supported), thus signifying that LMS use helps salespeople stay updated about their customer, product and market knowledge, which increases their ability to identify those leads who are most profitable.

5.1.1. Queue-based lead management systems

An analysis of just the queue-based dataset (i.e., respondents using queue-based LMSs) yielded an interesting outcome. Indeed, we found that the use of queue-based LMSs increased call quantity and was statistically significant (H8 supported), unlike our initial analysis of the general model. This may be because in a queue-based LMS, salespeople do not have to go back and forth filtering through a list of leads to determine which lead to call next. Instead, a queue-based LMS automatically assigns the next best lead for salespeople to call based on business-configured priorities. Hence, there is no downtime, which enables salespeople to always focus on making sales calls.

Additionally, we found that the use of queue-based LMSs has more impact on adaptive selling, technical skills and salesmanship skills than originally analyzed. Here, the use of queue-based LMSs, adaptive selling, lead follow-up intensity, technical skills and salesmanship skills explain a variance of 60.7% in inside sales performance as opposed to 55% in our initial analysis. This shows that the dataset available from list-based LMS users causes a detriment to our overall outcome. This significant improvement may be because queue-based LMSs allow management to implement effective and efficient business rules that can improve lead priority ranking, lead coverage and the quality of calls by salespeople. Here, we concluded that more research is needed to understand the specific dynamics of queue-based LMSs, and how queue-based approaches influence factors that improve inside sales performance.

5.2. Practical implications

The findings of this study provide industry practitioners with several strategic insights. For instance, we found that salespeople who effectively use LMSs increase their sales performance through task efficiency, improved sales behavior, and enriched information-based skills and knowledge. Using LMSs may help salespeople to keep abreast of their market and technical know-how. It also provides them with the proper tools to effectively demonstrate their products and services while sustaining quality conversations with leads. The information-based gains from LMSs allow salespeople to better understand the needs and purchasing abilities of leads and how to better sell to those leads.

Additionally, our research suggests that salespeople who tailor their sales presentations to fulfill the needs of their potential customers are more likely to close sales and ultimately improve sales performance. Accordingly, inside sales organizations should hire able salespeople who can effectively apply the information provided by their LMSs during interactions with leads.

Furthermore, we found that call quantity has no direct impact on sales performance but that it increased lead follow-up intensity, which in turn increases sales performance. This implies that not only do salespeople need to make many calls, they need to make many contact attempts to the right leads with consistency and speed. We advise managers on the need to communicate to their salespeople the importance of speed in their lead follow-up effort. Our findings show that immediacy is the most important factor in lead follow-up as it triggers the impact of lead follow-up intensity on sales performance. Contacting leads quickly after interest is shown allows salespeople to catch them at their highest point of interest, which could easily translate into sales.

Most importantly, inside sales organizations should leverage the benefits of queue-based systems to realize competency gains, task efficiency and enriched sales behavior. The use of queue-based LMSs can help salespeople increase the number of calls they make, increase their contact speed, increase phone contact attempts to leads, improve their contact ratio and decrease lead decay rate.

Finally, remote selling in today's rapidly evolving economy is becoming more complex. Salespeople need to devote additional effort, have persuasive and targeting skillsets, be very adaptive and equally knowledgeable about their leads, product category, and market settings to successfully advocate sales in the inside sales industry. Thus, the use of LMSs is a productive option for salespeople to integrate into their sales process. Inside sales managers looking to fully maximize the benefits of their technology investments should deploy LMSs built with the finest practices, and, most importantly, they should make sure their salespeople use these systems effectively.

5.3. Limitations and future research

While this study makes significant contributions to the understanding of sales technology approaches in the inside sales practice, it poses a few limitations that provide several opportunities for further research. First, we used a convenience sampling procedure, as our sample was represented by SMEs mainly in North America. This causes a considerable restriction on the generalizability of our findings and their applicability across larger organizations in the inside sales industry. Additionally, the findings of this study are based on a 108 sample size representation. Future studies should re-estimate our model with a larger sample size.

Second, to reduce response bias, we collected objective responses from sales managers and decision makers about their salespeople (i.e., how managers and decision makers perceive their salespeople's activities, behaviors, characteristics and performance). In doing so, we overlooked the fact that aspects such as the usage of LMSs are better reported on by salespeople who use the systems. Therefore, response bias may still exist. However, collecting data from managers and decision makers allowed us to collect a single response that was reported for an average of 10. This is because each sales manager was responsible for an average of 10 salespersons.

Third, we used a single item measure for call quantity. Although this method is acceptable, we could have used a more comprehensive measure. Thus, we call for further research with an extensive conceptualization of call quantity. Additionally, our survey did not collect enough data from list-based LMS users to enable a comparison of both LMSs. Hence we only compared the use of queue-based LMS to the general model. More research is needed for a better understanding of both LMS types.

Furthermore, our study did not explore moderating impacts of the use of LMS on sales performance because we did not consider this while collecting data for our research. Accordingly, we call on future research to consider modeling several moderating effects of technology usage on performance. It will be interesting to assess if the relationship between LMS use and sales performance is not mediated through adaptive selling, technical skills and salesmanship skill, but rather LMS use moderates the relationship between adaptive selling, technical skills and salesmanship skill and sales performance.

Finally, we believe that valuable research can be conducted to investigate the mediated impact of social media on IT usage and sales performance. Social media plays a key role in today's knowledge-intensive and smart selling environment (i.e., how salespeople use social media to discover potential customer needs or identify priority leads).

6. Final conclusions

Despite the rising importance of inside sales, the literature is short of knowledge on inside sales in general. Particularly, the literature lacks insights on technology usage practices, and effective lead engagement practices that can improve lead management outcomes, customer acquisition, and sales performance in inside sales. The current work attempts to fill this gap. We proposed that, when managing leads, LMSs that are built on best practices can curb the challenges faced by inside sales organizations. Accordingly, this study makes the following key contributions. First, we introduced and empirically validated a conceptual model based on the Technology-to-Performance Chain (TPC) of the Task-Technology-Fit (TTF) theory by Goodhue and Thompson (1995) that captures key inside sales performance drivers and enablers, and the impact of the use of LMSs on these drivers and enablers. We believe that this is the first empirical investigation covering all the proposed concepts in a single study. A PLS-SEM analysis provided support for nine (9) of our 11 proposed hypotheses. Second, we showed that LMS use affects inside sales performance via improving salespeople's adaptive selling, technical skills and salesmanship skills, and together these variables explain more than half (55%) of the variance of inside sales performance. We also uncovered a negative relationship between call productivity and inside sales performance, and highlighted that queue-based LMS users obtain better inside sales performance (compared to list-based LMS users). Finally, we offered an academic standpoint on the nature of inside sales and the major role that IT plays in their success; and educated practitioners on the key enablers of inside sales performance and effective IT usage approaches that can drive inside sales performance.

Acknowledgments

The work described in this study was supported by grants from Mitacs Canada (No. 310363).

Appendix A

Table A1
Indicators cross loadings for general model.

Indicators	Constructs					
	Adaptive selling	Call quantity	Use of LMS	Technical skills	Salesmanship skills	Sales performance
AS1	0.814	0.034	0.248	0.290	0.430	0.485
AS3	0.840	0.073	0.269	0.380	0.527	0.559
AS3	0.872	0.064	0.212	0.312	0.369	0.523
CP1	0.069	1.000	0.144	−0.136	0.022	0.099
LMSU1	0.220	0.157	0.817	0.304	0.221	0.266
LMSU2	0.113	0.072	0.713	0.270	0.034	0.124
LMSU3	0.196	0.129	0.795	0.164	0.287	0.242
LMSU4	0.327	0.085	0.815	0.291	0.279	0.207
TS1	0.378	−0.110	0.304	0.908	0.489	0.451
TS2	0.392	−0.080	0.343	0.875	0.454	0.510
TS3	0.184	−0.173	0.217	0.825	0.449	0.295
TS4	0.316	−0.125	0.201	0.761	0.549	0.360
SS1	0.374	0.085	0.072	0.430	0.813	0.418
SS2	0.502	0.085	0.208	0.445	0.805	0.506
SS3	0.392	−0.028	0.114	0.390	0.732	0.420
SS4	0.375	−0.058	0.417	0.492	0.778	0.458
SP1	0.550	0.090	0.210	0.499	0.523	0.873
SP2	0.409	0.023	0.175	0.298	0.439	0.728
SP3	0.503	−0.027	0.147	0.355	0.343	0.758
SP4	0.470	0.202	0.325	0.364	0.493	0.755

References

Abdolvand, M. A., & Farzaneh, S. (2013). Impact of sales experience and training on sales presentation skills between industrial salespersons. *Research Journal of Applied Sciences, Engineering and Technology, 5*(8), 2661–2670.
Ahearne, M., Hughes, D. E., & Schillewaert, N. (2007). Why sales reps should welcome information technology: Measuring the impact of CRM-based IT on sales effectiveness. *International Journal of Research in Marketing, 24*(4), 336–349.
Ahearne, M., Jelinek, R., & Rapp, A. (2005). Moving beyond the direct effect of {SFA} adoption on salesperson performance: Training and support as key moderating factors. *Industrial Marketing Management, 34*, 379–388.
Ahearne, M., Jones, E., Rapp, A., & Mathieu, J. (2008). High touch through high tech: The impact of salesperson technology usage on sales performance via mediating mechanisms. *Management Science, 54*(4), 671–685.
Ahearne, M., Mathieu, J., & Rapp, A. (2005). To empower or not to empower your sales force? An empirical examination of the influence of leadership empowerment behavior on customer satisfaction and performance. *Journal of Applied Psychology, 90*(5), 945–955.
Ahearne, M., Srinivasan, N., & Weinstein, L. (2004). Effect of technology on sales performance: Progressing from technology acceptance to technology usage and consequence. *Journal of Personal Selling and Sales Management, 24*(4), 297–310.
Anderson, S. A. (2007). *The moderating and mediating effects of computer self-efficacy on the sales self-efficacy/sales performance relationship. ProQuest dissertations and theses.* Ann Arbor: Nova Southeastern University. Retrieved from https://search.proquest.com/docview/304716972?accountid=14701.
Andreev, P., Heart, T., Maoz, H., & Pliskin, N. (2009). Validating formative partial least squares (PLS) models: Methodological review and empirical illustration. *ICIS 2009 proceedings* (pp. 193). .
Baldauf, A., & Cravens, D. W. (2002). The effect of moderators on the salesperson behavior performance and salesperson outcome performance and sales organization effectiveness relationships. *European Journal of Marketing, 36*(11/12), 1367–1388.
Barker, A. T. (1999). Benchmarks of successful salesforce performance. *Canadian Journal of Administrative Sciences, 16*, 95.
Behrman, D. N., & Perreault, W. D., Jr (1982). Measuring the performance of industrial salespersons. *Journal of Business Research, 10*(3), 355–370.
Boorom, M. L., Goolsby, J. R., & Ramsey, R. P. (1998). Relational communication traits and their effect on adaptiveness and sales performance. *Academy of Marketing Science Journal, 26*(1), 16–30.
Bradford, W., Johnston, W. J., & Bellenger, D. (2016). The impact of sales effort on lead conversion cycle time in a business-to-business opportunity pipeline. 6th international engaged management scholarship conference, 2016. Available at SSRN: https://ssrn.com/abstract=2866954 or doi:https://doi.org/10.2139/ssrn.2866954.
Burton-Jones, A., & Grange, C. (2012). From use to effective use: A representation theory perspective. *Information Systems Research, 24*(3), 632–658.
Carter, R. E., Henderson, C. M., Arroniz, I., & Palmatier, R. W. (2014). Effect of salespeople's acquisition-retention trade-off on performance. *Journal of Personal Selling & Sales Management, 34*(2), 91–111.
Chapman, G. (2018). *Inside sales vs. outside sales & the evolving art of communication*.
Chin, W. W. (1998). Commentary issues and opinion on structural equation modeling. *MIS Quarterly, 22*(1), Vii–Xvi.
Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). *Vol. 20*, 26 Hillsdale, NJ.
Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297–334.
D'Haen, J., Van den Poel, D., & Thorleuchter, D. (2013). Predicting customer profitability during acquisition: Finding the optimal combination of data source and data mining technique. *Expert Systems with Applications, 40*(6), 2007–2012.
D'Haen, J., Van den Poel, D., Thorleuchter, D., & Benoit, D. F. (2016). Integrating expert knowledge and multilingual web crawling data in a lead qualification system. *Decision Support Systems, 82*, 69–78.
Elkington, D., & Oldroyd, J. (2007). *How Much Time Do You Have Before Web-Generated Leads Go Cold? Lead Response Management Study*. Retrieved June 21, 2016, from http://www.leadresponsemanagement.org/lrm_survey.
Elkington, D., & Oldroyd, J. (2016). The best practices for lead response management. Retrieved June 3, 2017, from https://www.insidesales.com/wp-content/uploads/2016/04/LRM-info-graphic-poster-16-5x21-5.pdf?f4bf21&f4bf21.
Ferrell, L., Gonzalez-Padron, T. L., & Ferrell, O. C. (2010). An assessment of the use of technology in the direct selling industry. *Journal of Personal Selling & Sales Management, 30*(2), 157–165.
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39.
Franke, G. R., & Park, J.-E. (2006). Salesperson adaptive selling behavior and customer orientation: A meta-analysis. *Journal of Marketing Research (JMR), 43*(4), 693–702.
Gefen, D., Straub, D., & Boudreau, M.-C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems, 4*(1), 7.
Gessner, G., & Scott, R. A., Jr. (2009). Using business intelligence tools to help manage costs and effectiveness of business-to-business inside-sales programs. *Information Systems Management, 26*(2), 199.
Giacobbe, R. W., Jackson, D. W., Jr., Crosby, L. A., & Bridges, C. M. (2006). A contingency approach to adaptive selling behavior and sales performance: Selling situations and salesperson characteristics. *Journal of Personal Selling & Sales Management, 26*(2), 115–142.
Goad, E. A., & Jaramillo, F. (2014). The good, the bad and the effective: A meta-analytic examination of selling orientation and customer orientation on sales performance. *Journal of Personal Selling & Sales Management, 34*(4), 285–301.
Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly,* 213–236.
Groza, M. D., Locander, D. A., & Howlett, C. H. (2016). Linking thinking styles to sales performance: The importance of creativity and subjective knowledge. *Journal of Business Research, 69*, 4185–4193.
Hair, J. F., Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling ({PLS}-{SEM})*. Sage Publications.
Harmon, L. L., & Funk, D. S. (2014). *42 rules for building a high-velocity inside sales team: Actionable guide to creating inside sales teams that deliver quantum results.* Super Star Press.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.
Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path

modeling in international marketing. *New challenges to international marketing* (pp. 277–319). Emerald Group Publishing Limited.
Honeycutt, E. D., Jr. (2005). Technology improves sales performance–doesn't it? An introduction to the special issue on selling and sales technology. *Industrial Marketing Management, 34*(4), 301–304.
Hunter, G. K., & Perreault, W. D., Jr. (2006). Sales technology orientation, information effectiveness, and sales performance. *Journal of Personal Selling & Sales Management, 26*(2), 95–113.
Hunter, G. K., & Perreault, W. D., Jr. (2007). Making sales technology effective. *Journal of Marketing, 71*(1), 16–34.
Itani, O. S., Agnihotri, R., & Dingus, R. (2017). Social media use in B2b sales and its impact on competitive intelligence collection and adaptive selling: Examining the role of learning orientation as an enabler. *Industrial Marketing Management, 66*, 64–79.
Jaramillo, F., & Grisaffe, D. B. (2009). Does customer orientation impact objective sales performance? Insights from a longitudinal model in direct selling. *Journal of Personal Selling & Sales Management, 29*(2), 167–178.
Järvinen, J., & Taiminen, H. (2016). Harnessing marketing automation for B2B content marketing. *Industrial Marketing Management, 54*, 164–175.
Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer Research, 30*(2), 199–218.
Johlke, M. C. (2006). Sales presentation skills and salesperson job performance. *The Journal of Business & Industrial Marketing, 21*(5), 311–319.
Kadic-Maglajlic, S., Vida, I., Obadia, C., & Plank, R. (2016). Clarifying the influence of emotional intelligence on salesperson performance. *Journal of Business & Industrial Marketing, 31*, 877–888.
Keillor, B. D., Parker, R. S., & Pettijohn, C. E. (2000). Relationship-oriented characteristics and individual salesperson performance. *Journal of Business and Industrial Marketing, 15*(1), 7–22.
Ketchen, D. J., Jr., & Shook, C. L. (1996). The application of cluster analysis in strategic management research: An analysis and critique. *Strategic Management Journal,* 441–458.
Kuruzovich, J. (2013). Sales technologies, sales force management, and online infomediaries. *Journal of Personal Selling and Sales Management, 33*(2), 211–224.
Limbu, Y. B., Jayachandran, C., Babin, B. J., & Peterson, R. T. (2016). Empathy, nonverbal immediacy, and salesperson performance: The mediating role of adaptive selling behavior. *Journal of Business & Industrial Marketing, 31*, 654–667.
Maddox, K. (2013). IDC: Lead management a top investment for tech marketers. *BtoB, 98*(2), 0029.
Marketo (2008). *Success factors for highly effective inside sales teams*.
Miao, C. F., & Evans, K. R. (2012a). Effects of formal sales control systems: A combinatory perspective. *International Journal of Research in Marketing, 29*(2), 181–191.
Miao, C. F., & Evans, K. R. (2012b). Effects of formal sales control systems: A combinatory perspective. *International Journal of Research in Marketing, 29*(2), 181–191.
Monat, J. P. (2011). Industrial sales lead conversion modeling. *Marketing Intelligence & Planning, 29*(2), 178–194.
Moutot, J.-M., & Bascoul, G. (2008). Effects of sales force automation use on sales force activities and customer relationship management processes. *Journal of Personal Selling & Sales Management, 28*(2), 167–184.
Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial management data systems, 116*(9), 1849–1864.
Ohiomah, A., Benyoucef, M., & Andreev, P. (2016). Driving inside sales performance with lead management systems: A conceptual model. *Journal of Information Systems Applied Research, 9*(1), 4.
Ohiomah, A., Benyoucef, M., Andreev, P., Kuziemsky, C., Hood, D., & Le Bon, J. (2018). *Best practices for inside sales professionals: An historical analysis.* (Paper presented at the Academy of Marketing Science Annual Conference).
Ostrow, P. (2009). *Inside sales enablement: "Let them drink coffee"*.
Park, J. E., Kim, J., Dubinsky, A. J., & Lee, H. (2010). How does sales force automation influence relationship quality and performance? The mediating roles of learning and selling behaviors. *Industrial Marketing Management, 39*(7), 1128–1138.
Plouffe, C. R., Hulland, J., & Wachner, T. (2009). Customer-directed selling behaviors and performance: A comparison of existing perspectives. *Journal of the Academy of Marketing Science, 37*(4), 422–439.
Porter, S. S., Wiener, J. L., & Frankwick, G. L. (2003). The moderating effect of selling situtation on the adaptive selling strategy - selling effectiveness relationship. *Journal of Business Research, 56*(4), 275–281.
Pullins, E. B., Timonen, H., Kaski, T., & Holopainen, M. (2017). An investigation of the theory practice gap in professional sales. *Journal of Marketing Theory and Practice, 25*(1), 17–38.
Rapp, A., Agnihotri, R., & Forbes, L. P. (2008). The sales force technology–performance chain: The role of adaptive selling and effort. *Journal of Personal Selling & Sales Management, 28*(4), 335–350.
Rapp, A., Ahearne, M., Mathieu, J., & Schillewaert, N. (2006). The impact of knowledge and empowerment on working smart and working hard: The moderating role of experience. *International Journal of Research in Marketing, 23*(3), 279–293.
Rentz, J. O., Shepherd, C. D., Tashchian, A., Dabholkar, P. A., & Ladd, R. T. (2002). A measure of selling skill: Scale development and validation. *Journal of Personal Selling & Sales Management, 22*(1), 13–21.
Rivers, L. M., & Dart, J. (1999). Sales technology applications: The acquisition and use of sales force automation by mid-sized manufacturers. *Journal of Personal Selling & Sales Management, 19*(2), 59–73.
Robinson, L., Jr, Marshall, G. W., Moncrief, W. C., & Lassk, F. G. (2002). Toward a shortened measure of adaptive selling. *Journal of Personal Selling & Sales Management, 22*(2), 111–118.
Rodriguez, M., Ajjan, H., & Peterson, R. M. (2014). CRM/social media technology: Impact on customer orientation process and organizational sales performance. *Journal of Marketing Development & Competitiveness, 8*(1), 85–97.
Román, S., & Iacobucci, D. (2010). Antecedents and consequences of adaptive selling confidence and behavior: A dyadic analysis of salespeople and their customers. *Journal of the Academy of Marketing Science, 38*(3), 363–382.
Román, S., & Rodríguez, R. (2015). The influence of sales force technology use on outcome performance. *The Journal of Business & Industrial Marketing, 30*(6), 771–783.
Rutherford, B. N., Marshall, G. W., & Park, J. (2014). The moderating effects of gender and inside versus outside sales role in multifaceted job satisfaction. *Journal of Business Research, 67*(9), 1850.
Sabnis, G., Chatterjee, S. C., Grewal, R., & Lilien, G. L. (2013). The sales lead black hole: On sales reps' follow-up of marketing leads. *Journal of Marketing, 77*(1), 52–67.
Seley, A., & Holloway, B. (2008). *Sales 2.0: Improve business results using innovative sales practices and technology.* John Wiley & Sons.
Singh, R., & Koshy, A. (2010). Determinants of B2B salespersons' performance and effectiveness: A review and synthesis of literature. *Journal of Business and Industrial Marketing, 25*, 535–546.
Singh, R., & Venugopal, P. (2015). The impact of salesperson customer orientation on sales performance via mediating mechanism. *Journal of Business & Industrial Marketing, 30*(5), 594–607.
Smith, T. M., Gopalakrishna, S., & Chatterjee, R. (2006). A three-stage model of integrated marketing communications at the marketing–sales interface. *Journal of Marketing Research, 43*(4), 564–579.
Speier, C., & Venkatesh, V. (2002). The hidden minefields in the adoption of sales force automation technologies. *Journal of Marketing, 66*(3), 98–111.
Sundaram, S., Schwarz, A., Jones, E., & Chin, W. W. (2007). Technology use on the front line: How information technology enhances individual performance. *Journal of the Academy of Marketing Science, 35*(1), 101–112.
Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *JITTA: Journal of Information Technology Theory and Application, 11*(2), 5.
Van der Stede, W. A., Young, S. M., & Chen, C. X. (2005). Assessing the quality of evidence in empirical management accounting research: {the} case of survey studies. *Accounting, Organizations and Society, 30*(7–8), 655–684.
VanillaSoft (2014). *4 ways queue-based lead management is shaping the inside sales industry.* VanillaSoft. Retrieved June 3, 2017, from https://www.vanillasoft.com/resources/white-papers/queue-based-lead-management.
Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204.
Verbeke, W., Dietz, B., & Verwaal, E. (2011). Drivers of sales performance: A contemporary meta-analysis. Have salespeople become knowledge brokers? *Journal of the Academy of Marketing Science, 39*(3), 407–428.
Wachner, T., Plouffe, C. R., & Grégoire, Y. (2009a). SOCO's impact on individual sales performance: The integration of selling skills as a missing link. *Industrial Marketing Management, 38*(1), 32–44.
Wachner, T., Plouffe, C. R., & Grégoire, Y. (2009b). SOCO's impact on individual sales performance: The integration of selling skills as a missing link. *Industrial Marketing Management, 38*(1), 32–44.
Weitz, B. A., Sujan, H., & Sujan, M. (1986). Knowledge, motivation, and adaptive behavior: A framework for improving selling effectiveness. *The Journal of Marketing, 50*(4), 174–191.
Wold, H. (1985). Partial least squares. *Encyclopedia of statistical sciences*.
Zallocco, R., Pullins, E. B., & Mallin, M. L. (2009). A re-examination of B2B sales performance. *Journal of Business & Industrial Marketing, 24*(8), 598–610.

Alhassan, Ohiomah, MSc., is a PhD student in Electronic Business at the University of Ottawa, Canada. He holds an MSc in Electronic Business Technologies from the University of Ottawa and a BSc in Business Information Systems from the University of East London, UK. His research interests include inside sales performance, data-driven analytics and business intelligence.

Andreev, Pavel Ph.D., is an Associate Professor and a coordinator of the Business Analytics and Information Systems Section at the Telfer School of Management. He has a Ph.D. from Ben-Gurion University in the Negev, Israel. His research is focused on the exploring the impacts of Information and Communication Technology (ICT) at the individual, team, organizational, and community levels.

Benyoucef, Morad Ph.D., is a Full professor in Management Information Systems at the Telfer School of Management, University of Ottawa, Canada. He holds a Ph.D. from Université de Montréal and an MSc from Rochester Institute of Technology. His research interests include online marketplaces, social commerce, e-health, and business process modeling.

David, Hood MA., serves as the President and Chief Executive Officer of Vanillasoft Inc. He is a successful software entrepreneur with extensive experience in finance, business development, and marketing. He holds a BSc in Biochemistry, a Master's Degree in International Affairs and graduated from the Owner-President Management program (OPM) of Harvard Business School.