Lead to Win: Recipes for Inside Sales Success

By

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Abstract

The role of sales has evolved over the last decade, mostly driven by technological and social changes. One major shift is the growth in importance and in size of the inside sales function. Inside sales are sales that are conducted remotely or virtually using one or more Information Technology (IT) tools without the traditional in-person interaction. Despite the growing importance of inside sales, studies that show the key determinants and practices that can improve inside sales success are rare and have tended to focus on determinants affecting individual salesperson performance. Moreover, existing approaches to customer acquisition in inside sales often rely on subjective intuition, expert suggestions and gut feeling, which often hurts the chances of qualifying and converting leads to sales, and eventually diminishes inside sales success. This research aims to address such shortcomings by: 1) investigating the key dimensions and determinants of inside sales success by summarizing the existing body of knowledge using a systematic review and meta-analysis; and 2) develop comprehensible lead conversion models that integrate the interplay of relevant determinants in the lead conversion process.

This doctoral research aims to: (1) Synthesize the literature and draw a big picture of B2B sales success by providing practitioners and scholars with a comprehensive state-of-the-art understanding of the determinants of B2B sales success and their significance in inside sales. (2) Identify and validate several key lead engagement factors crucial for inside sales success. (3) Demonstrate the potential of data-driven analytics by collecting multiple historical datasets from several companies representing different industries. This includes investigating and discovering new insights that will improve lead conversion outcomes, which contributes to the literature on the ongoing discussion of effective sales pipeline management. (4) Provide sales practitioners with comprehensible lead conversion models that integrate industry specific behavior and performance of salespeople, characteristics of leads and/or prospects, and workflow strategy aspects. This will help sales practitioners to better understand problems and opportunities in lead management, take proactive actions, and improve their sales success.

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List of Abbreviations

AI:	Artificial Intelligence
AIC:	Akaike Information Criterion
AS:	Adaptive Selling
ANN:	Artificial Neural Network
AVE:	Average Variance Extracted
BI:	Business Intelligence
B2B:	Business-to-Business
B2C:	Business-to-Consumer
CA:	Cronbach's Alpha
CART:	Classification and Regression Tree
CB-SEM:	Covariance-based Structural Equation Modelling
CR:	Composite Reliability
CRM:	Customer Relationship Management
CQ:	Call Quantity
F^2:	Effect Size
HTMT:	Heterotrait-Monotrait
ICT:	Information and Communications Technology
IS:	Information System
IT:	Information Technology
LDA:	Latent Dirichlet Allocation
LFU:	Lead Follow-Up Intensity
LMS:	Lead Management Systems
LR:	Logistic Regression
ML:	Machine Learning
NB:	Naive Bayes
PLS:	Partial Least Squares
PLS-SEM:	Partial Least Square Structural Equation Modelling
R^2:	Coefficient of Determination
Q^2:	Predictive Relevance
RF:	Random Forest
SEM:	Structural Equation Modelling
SFA:	Sales Force Automation
TS:	Technical Skills
SLR:	Systematic Literature Review
SME:	Small and Medium Enterprises
SMOTE:	Synthetic Minority Oversampling Technique
SP:	Sales Performance
SS:	Salesmanship Skills
TPC:	Technology-to-Performance Chain
TTF:	Technology-Task-Fit
W:	Weight
VIF:	Variance Inflation Factor

Chapter 1: Introduction

The contemporary sales function has welcomed an innovative era of buyer and seller interaction (Chapman, 2018; Pullins *et al.*, 2017). The increasing cost of field sales, as well as rapid advances in technology and rising buyer expectations have contributed to the rapid growth of inside sales (Gessner & Scott Jr, 2009; Rutherford *et al.*, 2014; Thaichon *et al.*, 2018). The term "Inside sales" originated in the 1980s (Harmon & Funk, 2014), to refer to selling practices conducted from a distance using one or more ICT (Information and Communications Technology) tools, as opposed to the traditional face-to-face interactions with customers (i.e., field sales or outside sales) (Rapp *et al.*, 2012). Although the early adoption of inside sales involved inside salespeople supporting outside salespeople, nowadays, many organizations have completely adopted the inside sales method from prospecting to account management (Harmon & Funk, 2014). For most organizations, inside salespeople are tasked with customer acquisition activities, which include sales lead generation and qualification, calling and engaging with leads, and arranging contacts or meetings for outside salespeople, account managers and supervisors to close and convert to sales (Harmon & Funk, 2014; Zoltners *et al.*, 2013). Despite the noticeable potential of inside sales, little is known about the factors and practices that can improve inside sales success (Ohiomah *et al.*, 2019; Ohiomah *et al.*, 2018; Rutherford *et al.*, 2014).

1.1. Research Problem and Motivation

Although the relationship between several determinants and sales success has been validated in the literature (e.g., Churchill Jr *et al.*, 1985; Verbeke *et al.*, 2011), little is known about the importance of different determinants and practices in explaining sales success, particularly in the context of inside sales. The existing literature is characterized by three major limitations.

First, despite the importance of internal organizational determinants (e.g., technology, training and support, etc.), external customer determinants (e.g., trust, satisfaction, etc.) and external environmental determinants (competition, industry, etc.), comprehensive studies that show their role in sales success remain scarce and outdated. Even though the literature has investigated the determinants of sales success such as skills, behavior and attitudes of individual salespersons (Pullins *et al.*, 2017), there is a need to synthesize the recent literature to determine new and updated internal salesperson and organization as well as external customer and environment determinants of sales success.

Second, existing research efforts have been geared towards identifying sales success determinants for outside sales (Rutherford *et al.*, 2014), and have often underexposed the topic of inside sales (Harmon & Funk, 2014). We argue, as did other scholars, that success in inside sales may have different determinants than outside sales because of the variances in environment, organizational and situational contexts (Chapman, 2018; Singh & Koshy, 2010), hence existing research outcomes based on outside sales may not be transferable to the inside sales context (Churchill Jr *et al.*, 1985). Therefore, it will be interesting to uncover whether the era of insides sales has introduced new sales success determinants or changed the significance of existing ones, or if sales success determinants are different for inside sales and outside sales situations. There is now a sizable body of contemporary research to be reviewed and this research aims to do just that.

Third, lead qualification and conversion to sales is a core component of the inside sales process (Pullins *et al.*, 2017), yet, effective lead engagement remains a serious issue for practitioners (Järvinen & Taiminen, 2016; Ohiomah *et al.*, 2016; Sabnis *et al.*, 2013; Smith *et al.*, 2006). This is because decisions on lead engagement are often guided by subjective practices, which often impedes the chances of qualifying and converting leads to sales (Bohanec *et al.*, 2017; Ohiomah *et al.*, 2018; Yan *et al.*, 2015). Moreover, we note that inside sales practitioners require relevant insights on sales practices that can improve lead conversion outcomes. Data-driven analytics such as machine learning can help provide insights on sales lead conversion activities. We note that in spite of inside sales' high expectations from data-driven analytics, the applications remain limited. The increasing availability of data offers a great potential to use machine learning methods, techniques, and tools to improve the sales pipeline process and enhance lead conversion ratios (Eitle & Buxmann, 2019). In view of that, this research will employ data-driven analytics to provide inside sales practitioners with comprehensible, interpretable and explainable models to support their lead engagement activities and help improve lead conversion ratios.

1.2. Research Questions and Objectives

To address the abovementioned limitations in the inside sales literature, this doctoral research seeks to investigate two main research questions:

Research Question 1 (Q1): *What are the dimensions and determinants of inside sales success?* The specific objective is to:

- **Research Objective 1 (O1):** Summarize the existing body of knowledge using a systematic review and a meta-analysis of the literature in order to identify determinants that can improve inside sales success.

Research Question 2 (Q2): *How can data-driven analytics optimize lead engagement outcomes for inside sales?* The specific objectives are to:

- **Research Objective 2 (O2):** Conceptualize and empirically validate the key lead engagement factors for inside sales success.
- **Research Objective 3 (O3):** Develop lead conversion models that can recommend comprehensible, generic, and specific lead engagement strategies for inside sales success.

The first research question is motivated by the first 2 limitations while the second research question is motivated by the third limitation.

1.3. Research Contributions

The major contribution of this doctoral research is the **identification of sales success determinants and the recommendation of effective sales engagement strategies that can enhance inside sales success**. The major contribution is broken down as follows:

- Proposed an Integrative B2B Sales Success Model that showcases the key dimensions (i.e., salesperson, organization, customer and environment) and determinants and practices that facilitate the success of B2B sales (see Chapter 2). For that we conducted a systematic review of the existing body of knowledge using a meta-analysis of 139 related journal articles and 31 verified determinants of B2B sales success. Although the study focused on B2B sales, the findings are significant for inside sales because most inside sales designs in the literature are from the B2B domain. Moreover, our moderator analysis provides insights into the significance of each B2B determinant in the context of inside sales. Such insights were missing from the literature.

- 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 how the use of Lead Management Systems (LMSs) influences key lead engagement factors of inside sales performance (see Ohiomah et al., 2019, Chapter 3).

- Utilized a multi-industry dataset (representing 43 companies containing data on 47 million interactions with about 13 million leads) to suggest the best conditions for optimizing lead engagement outcomes in inside sales (see Ohiomah et al 2018, Chapter 4).

- Developed a conceptual model capturing the drivers of team based B2B sales by synthesizing existing knowledge through a scoping review. We then empirically validated the impact of the captured team-based drivers on team performance at each stage of the sales pipeline using multinomial regression on data representing the interactions of 4236 sales teams with 929,481 leads (see Chapter 5).

- Developed several lead conversion models using four machine learning classifiers, namely CART, LR, NB and RF, that integrate industry specific performance of salespeople, characteristics of leads and/or prospects and lead engagement strategy aspects. The proposed machine learning models foster a better understanding of the problems and opportunities in lead engagement for both the lead qualification and lead/opportunity management stages of the sales pipeline (see Chapter 6).

The minor contributions of this research include:

- Provided insights into the roles and functions of the evolving field of inside sales.

- Recommended technology use approaches that can maximize the impact of lead engagement practices on inside sales performance.

- Identified different stages of the sales pipeline from text data using text mining.

- Demonstrated the potential of data-driven analytics and the application of comprehensible and explainable machine learning methods in sales pipeline management using data from over 37 million interactions of salespeople with about 7.5 million leads covering several companies in different industries.

1.4. Related Publications

- Ohiomah, A., Benyoucef, M., & Andreev, P. (2020). A multidimensional perspective of business-to-business sales success: A meta-analytic review. Industrial Marketing Management, 90, 435-452.

- Ohiomah, A., Andreev, P., Benyoucef, M., & Hood, D. (2019). The role of lead management systems in inside sales performance. *Journal of Business Research*, *102*, 163-177.

- Ohiomah, A., Benyoucef, M., Andreev, P. Kuziemsky, C., Hood, D., & Le Bon, J., (2018). Best Practices for Inside Sales Professionals: An Historical Analysis. *Proceedings of the 2018 Academy of Marketing Science (AMS) Annual Conference.* May 23-25, 2018. New Orleans, LA, USA

- Haque, R, Ohiomah, A. A., Benyoucef, M., & Andreev, P. (2020). Drivers of team-based Inside Sales performance in B2B Selling: a Data Driven Study. *Industrial Marketing Management (Under Review, Minor Revision*)

- Ohiomah, A., Andreev, P., Benyoucef, M., & Hood, D. (2020). Lead to Win: Machine Learning Recipes for Inside Sales Lead Conversion. *Industrial Marketing Management* (*Submitted*, *Under Review*)

- Ohiomah, A., Benyoucef, M., Andreev, P., Kuziemsky, C., Hood, D., & Le Bon, J., (2018). Big Data Analytics for Inside Sales Lead Optimization, or Engaging Customers When It Matters the Most: An Abstract. *Proceedings of the2018 AMA Winter Academic Conference.* (Vol. 29, M-20). February 23-25, 2018. New Orleans, LA, USA

- Ohiomah, A., Andreev, P., & Benyoucef, M., (2017). A Review of Big Data Predictive Analytics in Information Systems Research. In *Proceedings of the Conference on Information Systems Applied Research ISSN* (Vol. 2167, p. 1508).

1.5. Thesis Outline

The remainder of this thesis is organized as follows. In the second chapter, we define sales success, and identify the key dimensions and determinants of B2B sales success. The third chapter demonstrates the nature of inside sales and the role IT plays in inside sales success. The fourth chapter discusses the best time management and lead calling practices for engaging with B2B and B2C leads. The fifth chapter discusses sales teams and the drivers of B2B sales team's performance in inside sales. The sixth chapter proposes lead conversion models that provide comprehensible and explainable insights on effective lead engagement practices for both the lead qualification and lead/opportunity management stages of the sales pipeline. Finally, this thesis by articles concludes with a short summary of the implications of our research findings for the inside sales literature and the practice of inside sales, as highlighted in the five articles.

Chapter 2: A Multidimensional Perspective of Business-to-Business Sales Success: A Meta-Analytic Review


Industrial Marketing Management
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A multidimensional perspective of business-to-business sales success: A meta-analytic review

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Article Abstract: The role and nature of business-to-business (B2B) sales has evolved since the end of the 20th century, mostly driven by technological, organizational and social changes. However, the literature has yet to catch up with that evolution. Particularly, the literature lacks contemporary studies that exclusively showcase the key determinants and practices that facilitate the success of B2B sales. Hence, we conduct a meta-analysis of the literature and summarize the results of 139 independent published studies from 1980 to 2019 that examined the relationship between several determinants and B2B sales success. Our results show that such success may be influenced by 31 different determinants associated with four dimensions of the selling process (i.e., salesperson, organization, customer, and environment). We also investigate the moderator effects of measurement source (subjective vs. objective), measurement items (single vs. multiple), industry context (goods vs. services), number of industries (single vs. multiple), sales function (inside sales vs. outside sales) and year of publication (before 2010 vs after 2010) between several determinants and B2B sales success. Our findings convey important implications for theory and practice on the key determinants of B2B sales success, as well as the conditions on which each determinant is effective. We also provide recommendations for further research on B2B sales success.

Keywords: Sales success; B2B sales; Meta-analysis; Competence

Note: This Chapter is an Author accepted manuscript submitted to the journal referred to above.

2.1.Introduction

Understanding the determinants of sales success has been a prominent topic in industrial sales and marketing research for decades (e.g., Churchill et al., 1985; Verbeke et al., 2011). The relationship between several determinants and sales success has been validated in the literature in the context of diverse selling situations. Churchill et al. (1985), for instance, identified role variables, skill, motivation, personal traits, aptitude and organizational and personal factors as key determinants of a salesperson's performance. Twenty five years later, Verbeke et al. (2011) investigated a wide spectrum of sales performance drivers and found that selling knowledge, adaptive selling, role ambiguity, cognitive aptitude, and work engagement (see Table 2.1 for definitions) had a significant impact on sales performance. Despite research advances in this area, there is still much to learn on the significance of different determinants in explaining sales success, particularly in the context of business-to-business (B2B) sales (in this paper, we use "B2B sales" to mean "industrial sales"). The existing literature is characterized by two major shortcomings.

First, the literature on sales success has mostly focused on the determinants of salespeople's individual performance or selling effectiveness (Jaramillo & Marshall, 2004). Pullins et al. (2017) suggested that determinants of sales success that are under the control of a salesperson, such as behavior and attitudes, have received considerable attention in the literature. However, comprehensive review studies that show determinants such as training, rewards, and management controls (i.e., factors that are not under the control of a salesperson) are few and have not been updated in recent years, even though successful sales interactions are highly dependent on organizational determinants (internal or related to the organization's external environment). Accordingly, there have been calls for research to investigate factors that influence a sales organization's overall success rather than just the success of a salesperson (e.g., Sullivan et al., 2012).

Second, research on sales success determinants has proposed a generic list of determinants for sales success (e.g., Churchill et al., 1985; Verbeke et al., 2011). However, despite conventional norms, salespeople do not all perform the same set of activities because industry, product, and/or organizational philosophy may differ across sales situations (Marshall et al., 1999; Singh & Koshy, 2010). Churchill et al. (1985) emphasized that the diversity of sales interactions, selling tasks, and responsibility across organizations may lead to inconsistencies and lack of external validity in research outcomes. Accordingly, Singh and Koshy (2010) suggested that future studies should focus on context specific selling situations while identifying determinants critical to sales success. Furthermore, the authors stressed that some previous findings on the determinants of sales success could not be exclusively applicable to B2B sales. Selling to businesses is highly complex, often lengthy, and involves multiple decision-making processes and participants (Verbeke et al., 2011), which is not the case when selling to individual customers. When selling to businesses, several factors are out of the control of salespeople, which might require them to dedicate more time and organizational resources, hence reducing their chances of success. Therefore, improving the success of B2B salespeople remains a major issue for sales researchers and practitioners (Frino & Desiderio, 2013; Singh & Koshy, 2010; Zallocco et al., 2009). Against this backdrop, several attempts have been made by scholars to extend the literature on B2B sales success determinants. For instance, using data collected from an interview with managers and salespeople, Zallocco et al. (2009), proposed a four cross-dimensional view (i.e., internally, externally, effectiveness, and efficiency) of assessing B2B sales success. Singh and Koshy (2010) theoretical review of the literature suggested several categories (e.g., cognitive, personality, situational, behavioral, communication, attribution) of determinants for B2B sales success. Despite the notable contributions of both studies (i.e., Singh & Koshy, 2010; Zallocco et al., 2009), much remains to be done. Particularly, we suppose that the literature can benefit from a more holistic and comprehensive synthesis study that is grounded in solid empirical analysis.

Moreover, recent advances in information technology, as well as an increasing competitive market environment have restructured the B2B sales function (Herjanto & Franklin, 2019), and revamped how salespeople approach and communicate with customers (Rutherford et al., 2014). Reports indicate that B2B customers now complete about 70% of their buying process online before reaching out to a sales representative (Forbes, 2017). Therefore, it is important to understand whether key sales success determinants have changed with this evolution.

Our work addresses the abovementioned shortcomings by answering the following question: *What are the dimensions and determinants of B2B sales success?* We believe that the current state of research that relies on respondents from B2B sales can benefit from an aggregation of empirical findings in order to identify the key determinants of B2B sales success, as well as their magnitude and direction of influence (i.e., positive or negative). The goal is to synthesize the literature and draw a big picture of B2B sales success by providing practitioners and scholars with a more comprehensive state-of-the-art understanding of the determinants of B2B sales success. This can help introduce new practices, policies and strategies to the sales function in order to improve the success of B2B sales.

Accordingly, this study advances the literature in three ways. (1) We summarize the existing body of knowledge using a systematic review of the literature in order to identify determinants of B2B sales success. (2) We conduct a meta-analysis using correlations of the shortlisted determinants, including a moderator analysis to provide insights into measurement characteristics and research contexts that could sway the relationship between determinants and B2B sales success. (3) We group these determinants based on each one's theoretical definition and operationalization, and then propose a four-dimensional model and a roadmap for current and future research on B2B sales success.

We begin this investigation with a definition of sales success (see Section 2). Then, the data collection and method of analysis are explained (see Section 3). Next, we present the results of the analysis (see Section 4). In Section 5, we identify and group significant determinants of B2B sales success and propose a B2B sales success model based on these determinants. We also highlight the contributions of this study to theory and practice, suggest further research opportunities, and discuss the limitations of this study.

2.2. What is Sales Success?

Sales success has been conceptualized in different ways with various terminologies (Singh & Koshy, 2010), including sales or salesperson performance (behavior and outcome), sales effectiveness, sales efficiency, and customer satisfaction. This has led to a lack of consensus and a misconceptualization regarding sales success. For instance, sales or salesperson performance is one of the most widely researched concepts in the sales literature (Limbu et al., 2016), and it has been used as a proxy for sales success (Plank & Greene, 1996). While sales success captures the performance of salespeople, the performance of salespeople does not reflect sales success, but rather may account for a portion of it. Walker et al. (1979) suggested that performance is reflected in good or bad behavior and/or characteristics of salespeople's influence towards achieving an organization's goals and objectives. This means that performance is reflective of a salesperson's behavior and contributions that affect sales outcomes, while sales success reflects not only individual behavior and contributions, but also includes the performance of organizational and environmental factors that strongly drive the achievements of a sales organization. These may include management policies, territory potential and competitive strategies that can be measured by indexes of organizational outcomes such as market share or sales volume (Singh & Koshy, 2010).

Our conceptualization of sales success aligns with Churchill et al. (1985, p. 116) description of sales effectiveness as *"a summary index of organizational outcomes for which an individual is at least partly responsible"*. Sales success captures the outcome of all sales tasks (i.e., from prospecting to aftersales services in either inside or outside sales) that contribute to ensure successful competitive business performance for organizations (Jaramillo & Marshall, 2004; Singh & Koshy, 2010). For the purpose of this research, we define *Sales Success* as *the level of achievement of sales goals and objectives within a specified period of time or according to a specified parameter, which can be based on results achieved by the sales organization, a sales project or sales task, or qualitative and quantitative results of salespeople*. Sales success can be measured using several indicators including sales volume, revenue, market share, sales effectiveness, new accounts created, closing rates, customer profitability, and profit margin for organizations (Churchill et al., 1985; Singh & Koshy, 2010; Sullivan et al., 2012).

2.3.Research Design

The design of this research started with a systematic review of the literature. The initial search yielded a corpus of 1338 studies, that were finally reduced to 139 studies after a thorough screening procedure. For the analysis, we followed a two-step approach in our investigation of the relationship between determinants and sales success. First, we conducted a tally of effect significance (i.e., informal vote counting) to identify key factors that have been investigated by selected studies (Card, 2015). In other words, we looked at the research models used in individual studies and identified which determinants have a "significant positive", "significant negative" and "non-significant" effect on sales success. The outcome of this procedure provided us with a shortlist of key determinants investigated by the selected studies. Only correlations for the shortlisted determinants were recorded for the second step (i.e., meta-analysis). Second, we conducted a meta-analysis using Pearson's correlation coefficient metric (i.e., *r-family* of effect size (Rosenthal, 1995)) between the shortlisted determinants and sales success.

2.3.1. Literature Search

A systematic review of the literature was conducted to identify relevant studies on sales success in the context of B2B sales. First, we conducted a keyword search on the ABI/Inform, Business Source Complete, Scopus and PsycARTICLES databases. We searched these databases for peer-reviewed studies published in English from 1980 through 2019 using the following keywords: *Sales, Salespeople, Selling, Sales Efficiency, Sales Effectiveness, Sales Performance,* and *Sales Success*. We used 1980 as a starting point because the sales environment changed dramatically since the 1980s (Harmon & Funk, 2014; Marshall et al., 1999; Thaichon et al., 2018). Second, we conducted the same keyword search on leading sales and marketing journals (i.e., *Journal of Marketing, Journal of Marketing Research, Journal of the Academy of Marketing Science, Journal of Business Research, European Journal of Marketing, Industrial Marketing Management, Journal of Personal Selling and Sales Management, Journal of Applied Psychology and Academy of Management Journal*) to make sure not to miss key articles. Our search yielded an initial output of 1338 studies after removal of duplicates across the databases used. After the initial search yielded 1338 studies, the three authors had to review the title and abstract of each study. Two authors voted "relevant" or "not relevant" for each article (i.e., whether or not the study investigated sales success in any form), and the third author mitigated conflicted studies in situations when there was no unanimous consensus. There were almost no conflicts. After an assessment of the relevance of these 1338 studies through their titles and abstracts, 744 studies were removed, leaving 594 studies for the next step of our analysis.

We followed Moher et al. (2009) and Okoli (2015) systematic review and meta-analysis guidelines. During our practical and quality screening, we first evaluated the research settings where data were collected by the selected studies. To keep the focus on B2B sales, we only included studies that reported collecting data from B2B settings (i.e., B2B salespeople or managers as respondents), or studies with a majority of respondents being B2B salespeople or managers. Particularly, we removed all studies that were primarily conducted within retail sales and B2C sales settings. Also, we excluded prior sales success review papers to avoid bias and duplication of studies used for our meta-analysis. However, we considered other review papers when discussing our findings for comparative insights. Furthermore, we only included empirical studies the results of which were statistically validated and justified (i.e., all conceptual studies were excluded). Finally, we only included studies where the dependent variable measured a sales outcome (e.g., performance, effectiveness, etc.) at the individual and organisational levels. We only included studies that reported one or more independent-dependent variable association. As a result, 139 studies were selected for the coding procedure.

2.3.2. Coding Procedure

We created a coding manual that captures the detailed information needed from each study. We assigned a unique ID to each study, which was recorded along the complete citation of the paper. The studies measured the relationship between one or more determinants and sales success. We coded our studies in five steps as follows. (1) We extracted each determinant (i.e., ascendant, mediator, moderator, direct) and the sales success variable from each study. (2) We coded each positively statistically significant relationship of each determinant in each study as "+", each negatively statistically significant relationship as "-" and each non-significant relationship as "ns". (3) We used an informal vote counting technique (see Card (2015)) and selected independent variables that had more than three direct or indirect relationships with sales success. Informal (or conventional) vote counting involves the use of majority rules measures based on the significance of relationships between 2 variables (positive, negative and non-significant). Under this setting, a positive effect can be concluded if more studies find a significant positive effect than nonsignificant and or significant negative effects. Eventually, we generated a shortlist of commonly investigated sales success determinants. (4) We carefully reviewed and extracted the theoretical and operational definition of each shortlisted determinant. These definitions were reviewed and discussed by the authors in order to group the shortlisted determinants into their corresponding categories. (5) We retrieved all the required information from each study for determinants, relationship direction, data collection information, reliability measures, effect sizes (i.e., Pearson's correlation) and study descriptors needed for moderator analysis and entered this information into a database.

2.3.3. Informal Tallying of Significance

After extracting and coding the direction of each significant determinant, we generated a shortlist of sales success determinants that recorded three or more relationships (i.e., we only considered determinant that were analyzed in more than three studies). We then used the following formula to weigh each independent variable:

$$\boldsymbol{W} = \frac{+\,\mathbf{n}^2}{\boldsymbol{N}}$$

where + *n* is the number of positively significant relationships of each determinant *n*, and *N* is the total number of validated relationships (positive, negative and non-significant) for determinant n. We squared the number of positively significant relationships of each determinant because we seek to produce weight value that represent not just the simple traditional ratios of significantly positive relationships but also the number of studies that have tested the relationship for each determinant.

2.3.4. Effect Size Metric

We used Pearson's correlation *r* as a metric for our meta-analysis. Pearson's correlation assumes that the relationships between two variables are straightforward and are independent of other variables in a research model (Hunter & Schmidt, 2004). We used this metric because our meta-analysis focuses on bivariate relationships between determinants and sales success. Furthermore, correlations were the most commonly reported metric in the selected studies because they are easy to interpret. Correlations have been previously implemented for meta-analyses in the sales and marketing literature (e.g., Kirca et al., 2005; Verbeke et al., 2011). Four studies were dropped at this stage because they did not report correlations or other metrics like *t* or *F* statistics that can be converted into correlations (e.g., Plouffe et al., 2014).

2.3.5. Bivariate Analysis

We employed MIX 2.0 meta-analysis software (Bax, 2017) for our bivariate analysis. We used Hunter and Schmidt (2004) random-effects model to estimate for effect sizes and confidence intervals. The random-effects model assumes that variability in findings from studies may be initiated by the sampling of studies and sampling of respondents within studies. Unlike a fixed-effect model that assumes that a ''true'' correlation value between a determinant and the dependent variable underlies all studies in the meta-analysis, the random-effects model assumes that a potential moderator may cause deviation in effect sizes (Jaramillo et al., 2007).

Consistent with previous meta-analyses in sales and marketing, we applied Fisher's r-to-z transformation (Rosenthal, 1991) for the correlations by weighing each correlation for the sample size to improve reliability and minimize a possible difference with the exact correlation that is free of artifacts (Goad & Jaramillo, 2014; Hunter & Schmidt, 2004; Verbeke et al., 2011). We also provided information on average correlations in their raw form for each determinant. The MIX 2.0 software adjusts for sampling error by weighing each transformed correlation according to its applicable sample size. We used *Wald z test* to assess the statistical significance of mean effect size. In addition, a *Q-statistics* chi-squared test was computed to assess for heterogeneity in true correlations between studies for each determinant. The effect size is heterogeneous if the sampling variance is significantly greater than zero.

Following procedures used in the marketing literature, we treated correlations from different samples within a single study as independent observations (Franke & Park, 2006; Goad & Jaramillo, 2014). Although some studies report multiple effects for each determinant with sales success, we sought to extract one effect size per study for each determinant, except for cases when multiple samples were used in each study, or when the conceptualization of the determinant was based on more than one variable. For instance, in cases where both behavior and outcome performance were used as a measure of sales success, we only used effect size with outcome performance. This is because outcome performance reflects the outcome of the activity and behavior performance. In addition, when a single study reports multiple effect sizes based on different sales success measures by the same respondent, we averaged these multiple effect sizes.

2.3.6. Moderator Analysis

We conducted a moderator analysis in order to go beyond just considering bivariate correlations for our meta-analysis. The moderator analysis was performed using the difference in measurement methods and research context to account for the difference in effect sizes. Other methods for analyzing the effect of moderators (e.g., model estimation and model specification) do not apply to our research because our study only considers bivariate analysis, hence are unaffected by model specification (Henard & Szymanski, 2001). We selected the following measurement factors: (i.e., self-report versus manager-report; subjective versus objective performance measure; single-item versus multi-item performance measure) and research contextual factors (i.e., selling goods versus selling services; single industry versus multiple industry data sources; inside sales versus outside sales function; and publications before 2010 versus after 2010). We selected these moderators because they were reported by all the studies under investigation (i.e, we did not consider potential moderators that were not reported by all the studies in our investigation). Moreover, the selected moderators have theoretical justifications to serve as moderating factors in the sales and marketing research (see Franke & Park, 2006; Goad & Jaramillo, 2014; Henard & Szymanski, 2001; Verbeke et al., 2011). We believe these moderators have variances for determinants and will allow for comparison of the correlations for determinants.

Self-report vs. Manager-report: The strength of the association between success and each determinant may differ based on whether success was assessed by the salesperson (i.e., self-report) or by the salesperson's manager (i.e., manager-report) (Verbeke et al., 2011). As reported in the literature, individuals are normally biased when they are asked for a self-assessment, which may lead to an upward bias in the outcome including social disability response bias and other types of biases (Jaramillo & Marshall, 2004). Thus, it is expected that when success is assessed using self-report, the effect sizes of determinants will be stronger than when success is assessed from the manager's perspective (Verbeke et al., 2011).

Objective report vs. Subjective report: Objective reports based on operational data such as sales quota, profit margin on sales, and win vs. loss are part of standard bookkeeping procedures performed by organizations and are considered accurate and bias-free since they exclude perceptions and opinions (Henard & Szymanski, 2001). But subjective reports such as self-report and manager-report of success are drawn from subjective perceptions and assessments and thus are likely to reflect individual bias and/or inaccurate information. It is expected that subjective reports may overestimate or underestimate success and may have different effect sizes between determinants and success.

Single-Item vs. Multi-Item: Multi-item scales such as those introduced by Behrman and Perreault (1982) can be effective in capturing success at a comprehensive level. Compared to single-item scales, multi-item scales may result in stronger effect sizes for determinants of sales success. Single-item scales might only capture one indicator of sales success and as a result may yield to lower effect sizes for each sales success determinant. In addition, our proposed definition of sales success is multidimensional, thus multi-item scales would result in a stronger and more reliable effect size.

Selling goods vs. Selling services: Compared to goods, services are more intangible, highly inconsistent and could require a higher degree of customization (based on different customer expectations) (Anderson et al., 1997). The organizational resources needed for such customization usually result in higher sales costs and lower sales outcomes (Anderson et al., 1997). Selling goods is less complex because customers can easily assess information about their buying needs and preferences before the sales conversation (Verbeke et al., 2011), which may increase sales efficiency and overall outcome. We expect that effect sizes for determinants will vary when selling goods vs. services.

Single industry vs Multiple Industry: Scholars suggest that studies that use data samples from a single industry may have a larger correlation effect sizes (Crosno & Dahlstrom, 2008; Geyskens et al., 1998; Ketchen Jr et al., 1997). Conversely, studies using multiple industries for their investigations will have smaller correlation effect sizes (Crosno & Dahlstrom, 2008; Geyskens et al., 1998). In addition, sampling data from multiple industries could improve external validity of research outcomes because of the possible presence of a higher and diverse number of organizations for a reliable representative sample (Crosno & Dahlstrom, 2008; Ketchen Jr et al., 1997). Hence, we assume that studies that evaluate relationships between determinants with sales success using data samples form a multiple industry may have lower correlation sizes with sales success. To the best of our knowledge, no study has explored the moderating effect of the number of industries while reviewing sales success determinants.

Inside sales vs. Outside sales: The practice of B2B selling can be either Inside sales (i.e., sales conducted remotely using one or more information technologies) or Outside sales (traditional sales involving face-to-face interaction with customers) (Rapp et al., 2012). Because contemporary B2B sales are technology driven, the inside sales function has grown in size and significance (Rutherford et al., 2014; Thaichon et al., 2018). Inside salespeople are in a better position to use the full length and breadth of technology tools available to them to interact with customers remotely (mostly from their respective organizations), and to get the organizational support facilities they require. On the other hand, the nature of outside sales requires that salespeople work away from the organization. Thus, outside salespeople will not have immediate access to intraorganization communication and support services that may improve performance. Furthermore, the number of interactions needed for a successful sale with business customers is on the rise (Ohiomah et al., 2019). Thus, while outside salespeople need to travel and make multiple visits to customers, inside salespeople can remotely initiate contact with customers and gather the necessary information, which will make inside salespeople more efficient. Moreover, outside salespeople are able to meet customers face-to-face and thus are able to build trust and a better rapport, as well as sense the emotional cues of customers more effectively. Furthermore, most published determinants of sales success to date were defined and validated using data from outside salespeople. Hence, we believe that it is crucial to verify the differences, if any, between determinants and B2B sales success in the context of inside sales and outside sales. We believe that correlation effect sizes for determinants and B2B sales success will differ if data was collected from B2B inside salespeople or outside salespeople.

Publication Before 2010 vs After 2010: To add to our understanding of whether key sales success determinants have changed with the evolution in industrial selling, we consider the year of publication as a potential moderator that may affect the magnitude of effect size. We believe that effect sizes will differ for different determinant based on the advancement and importance of that determinant over time. We considered every publication before 2010 and publications after 2010. Here, all articles published in 2010 are grouped with studies published before 2010. We selected these two time points because we aim to capture the changes if any for all studies that were published after the meta-analysis by Verbeke et al. (2011).

We used regression procedures to test for the abovementioned moderators on corrected correlations. For each regression, a coefficient was used to test if the moderator variable was a statistically significant predictor of effect size.

2.4. Analysis and Results

In this section, we first present the results of our tallying of significance for the shortlisted determinants, and then we present the results of the effect size of each determinant with sales success (i.e., bivariate analysis). Subsequently, we show the results of the difference in effect sizes across different moderators. Our review of the literature shows that sales success has been assessed at four levels: *salesperson*, *organizational*, *customer,* and *environmental* levels. In the 139 studies we selected for the analysis, we identified over 25 different variables for measuring sales success.

For instance, scholars have used Behrman and Perreault (1982) measure items to assess behavior performance (e.g., Schwepker & Good, 2011), outcome performance (e.g., Chakrabarty et al., 2013), performance with customers (e.g., Hunter & Perreault Jr, 2006), relationship-building performance (e.g., Hunter & Perreault Jr., 2007), and other objective measures such as commission, sales volume and market share, leading to inconsistent outcomes in the literature and a lack of consensus about how to assess sales success. This validates our wide-ranging definition of sales success which conveys the achievement of sales goals at different levels of the organization. Nevertheless, we call on further research to develop a framework for choosing sales success measure based on specific criteria such as: research scope, research objective, method of research (i.e., qualitative or quantitative) data sources, and level of investigation etc. Such framework will serve as a guide that can help future scholars identify the right sales success measure to implement for their investigations.

2.4.1. Key Determinants of B2B Sales Success

To identify the key determinants of B2B sales success, we extracted each independent variable and the sales success variable from each study. We identified nearly 700 validated direct and indirect (ascendant, mediator) relationships with sales success from over 200 different determinant variables. We constructed the foundational definition of each of these constructs (see Table 2.1) in order to categorize the determinants using keyword similarity as well as semantic similarity of their definitions.

Table 2.1 Appears here

Our informal tallying of significance yielded 35 determinants of B2B sales success (see Table 2.2). Table 2.2 shows that salesperson determinants were the most investigated relationships with sales success. We found that adaptive selling (total number of effects (*N)* = 40), and customer orientation (*N* = 29) were the most investigated salesperson determinants of sales success. Meanwhile, adaptive selling (weight (*W)* = 34.2), customer orientation (*W* = 19.9), self-efficacy (*W* = 17.1) and effort (*W* = 17.1) were the most significant salesperson determinants of sales success based on the number of significant positive relationships with sales success. Furthermore, organizational determinants were the second most investigated relationships with sales success. Technology usage (*N* = 20, *W* = 20) was the most investigated and significant organizational determinant of sales success.

Table 2.2 Appears here

2.4.2. Bivariate Analysis

After reviewing the correlations between the determinants in Table 2.2 and sales success, we recorded 443 correlations from 140 samples, representing about 29,000 salespeople and approximately 5000 managers and supervisors. Our bivariate analysis indicates that 31 out of 35 determinants are significantly correlated with B2B sales success. Table 2.3 reports that gender, education, role conflict and competitor influence have no significant correlated effects with B2B sales success. Additionally, all significant ($p < 0.05$) determinants (see Table 2.3) were positively correlated except for role ambiguity which was negatively correlated with B2B sales success (r = -0.23). Our analysis showed strong correlations with B2B sales success for interpersonal skills (r = 0.40), technical skills (r = 0.40), salesmanship skills (r = 0.44) and customer trust (r = 0.48). Based on Cohen (1969) statistical power classification of effect sizes, our results indicate that 21 of the significant determinants had a significantly lower correlation with B2B sales success ($0.10 < |r| < 0.30$) and 9 determinants have medium correlations with B2B sales success ($0.30 < |r| < 0.50$).

Table 2.3 Appears here

2.4.3. Moderator Analysis

In this paper, we only report results of moderator analysis for determinants with at least 30:70 variation between group differences for at least one moderator. This is because some variables do not have sufficient variance between the groups of reported moderators. For instance, about 85% of the studies that investigated customer orientation, reported selling services and about 15% report selling Goods or Both. This extreme class imbalance will not allow for a reliable comparative analysis. We believe that any variable that has at least 30:70 variation in groups for that moderators will provide a reliable regression result. This will exclude determinants with imbalanced distributions between classes and remove bias from our findings. Four determinants had an insufficient number of distributed observations and were excluded from the analysis. Hence, Table 2.4 only shows the moderator analysis for the remaining 31 determinants. The results presented in Table 2.4 suggest that 31 moderator regression models account for statistically significant variance in correlation effect size between a determinant and B2B sales success.

Self-report vs. Manager-report of success: Table 2.4 shows that 6 determinants had enough observations that allow for a comparison between self and manager reports. Technical skills (β = -0.23, p<0.01) had a significant lower correlation effect with sales success when reported by managers thus signifying that salespeople appraise their technical knowhow higher than their managers perceive. In addition, our analysis shows that market and technology dynamism (β = 0.93, P <0.001) is highly correlated with sales success when apprised by sales managers.

Subjective report vs. Objective report of success: Subjective versus objective performance measures can influence the relationship between several determinants and sales success. In line with our expectations, the following determinants were found less influential when success was reported from objective measures: effort (β = -0.42, p <0.001), experience (β = -0.42, p <0.001), self-efficacy (β = -0.31, p <0.001), technical skills (β = -0.20, p <0.001), activity control (β = -0.72, p <0.001), leadership (β = -0.48, p <0.001), supervisory trust (β = -0.33, p <0.01), and technology usage (β = -0.56, p<0.001). This is because objective measures such as market share capture outcomes that are affected by the external environment, which is not under the control of salespeople. Moreover, job commitment (β = 0.60, p<0.001), intrinsic motivation (β = 0.32, p<0.001), as well as market and technology dynamism (β = 0.72, P <0.01) correlated higher with sales success when sales success is assessed objectively.

Single-item vs. Multi-item measures of success: The regression results indicate that the strength of the correlation between several determinants and sales success vary based on whether it is a single-item or a multi-item measure of success. Our findings indicate that the correlation effect between sales success and the following determinants increases when broader sets of sales success measures are used; job commitment (β = 0.64, *p* <0.001), self-efficacy (β = 0.39, *p* <0.001) and technology usage (β = 0.52, *p* <0.001). Additionally, we found that the relationship between outcome control and multi-item measures of sales success was lower (β = -0.66, *p* <0.001).

Selling goods vs. Selling services: We noticed that several studies reported collecting data from both sellers of goods and services. As a result, we excluded studies that reported "Both" for this analysis to avoid ambiguity. As anticipated, our results revealed that the correlation between adaptive selling (β = -0.58, *p* <0.001) and organization support (β = -0.39, *p*< 0.01) were significantly weaker with sales success when selling services. In addition, the results suggested a significantly stronger relationship between effort (β = 0.25, *p* <0.01), experience (β = 0.30, *p*

<0.001), job satisfaction ($\beta = 0.44$, $p < 0.05$), role ambiguity ($\beta = 0.32$, $p < 0.01$) and sales success when selling services.

Single industry vs Multiple industry: Contrary to our belief, our analysis shows that job commitment ($\beta = 0.82$, $p < 0.001$), customer orientation ($\beta = 0.46$, $p < 0.001$), age ($\beta = 0.38$, $p < 0.001$), effort ($\beta = 0.21$, $p < 0.001$), extrinsic motivation ($\beta = 0.50$, $p < 0.01$), salesmanship skills ($\beta = 0.45$, $p < 0.001$), leadership ($\beta = 0.24$, $p < 0.001$), organizational support ($\beta = 0.68$, $p < 0.001$), technology usage ($\beta = 0.53$, $p < 0.001$), and training ($\beta = 0.61$, $p < 0.001$) evince a higher correlation effect size with sales success when studies involve multiple industries. This may be because using multiple industries will produce more variation in the data (Geyskens et al., 1998), thus correlation effect sizes may be stronger in B2B selling situations. Moreover, goal orientation ($\beta = -0.64$, $p < 0.001$), job satisfaction ($\beta = -0.59$, $p < 0.001$) and technical skills ($\beta = -0.43$, $p < 0.001$) pronounced a lower effect correlation size with success when data from multiple industries is used.

Inside sales vs. Outside sales: Several studies reported collecting data from both inside sales and outside sales; hence, we also excluded studies who reported “Both” for this analysis. Our analysis showed a significantly stronger correlation effect size for experience ($\beta = 0.28$ $p < 0.01$), job satisfaction ($\beta = 0.51$ $p < 0.01$), salesmanship skills ($\beta = 0.44$ $p < 0.001$), organization support ($\beta = 0.83$ $p < 0.001$), technology usage ($\beta = 0.53$ $p < 0.001$), training ($\beta = 0.49$ $p < 0.01$), customer satisfaction ($\beta = 0.38$ $p < 0.01$), and relationship quality ($\beta = 0.73$ $p < 0.001$), when the selling task is carried out remotely. Moreover, the analysis revealed a weaker correlation effect size between sales success and adaptive selling ($\beta = -0.24$ $p < 0.01$), effort ($\beta = -0.15$ $p < 0.05$), goal orientation ($\beta = -0.52$ $p < 0.01$), role ambiguity ($\beta = -0.35$ $p < 0.01$), self-efficacy ($\beta = -0.37$ $p < 0.001$), technical skills ($\beta = -0.32$ $p < 0.001$) and capability control ($\beta = -0.61$ $p < 0.001$) for selling remotely. The positive and negative direction of these correlation effect sizes lead us to conclude that indeed, some determinants of B2B sales success are stronger when selling remotely, while others are stronger when selling face-to-face.

Publication Before 2010 vs Publication After 2010: Our analysis reveals that there are significant differences between the two periods. Particularly, we found that experience ($\beta = 0.41$, $p < 0.001$), job satisfaction ($\beta = 0.45$, $p < 0.001$), intrinsic motivation ($\beta = 0.34$, $p < 0.001$) and outcome control ($\beta = 0.32$, $p < 0.001$) had significantly stronger correlation with sales success for studies published after 2010. While, effort ($\beta = -0.14$, $p < 0.001$), role ambiguity ($\beta = -0.36$, $p < 0.001$), technical skills (β = -0.36, p <0.001), organizational support (β = -0.37, p <0.001), relationship quality (β = -0.43, p <0.001) and competitor influence (β = -0.79, p <0.001) had a significantly lower correlation size with sales success for studies published after 2010. This suggest that the significance of some determinants may have changed overtime. For instance, salespeople's effort was correlated with lower levels of sales success for studies published in the last decade. This makes sense because number of calls has in most cases been a key measure of a salesperson's effort in the literature, however recent studies (e.g., Ohiomah et al., 2019) have suggested that salesperson's effort had no significant impact on higher levels of sales success, and that salespeople need to focus more on making quality rather than quantity calls that could improve sales success.

Table 2.4 Appears here

2.5.Discussion and Implications

The literature lacks contemporary studies that exclusively showcase the key determinants and practices that facilitate the success of B2B sales. Accordingly, this study summarized the existing body of knowledge using a systematic review of the literature. We selected 139 related journal articles and shortlisted 35 verified determinants of B2B sales success. We also conducted a meta-analysis using correlations of the shortlisted determinants, including a moderator analysis to provide insights into measurement characteristics and research contexts that could sway the relationship between determinants and B2B sales success.

2.5.1. Implications

Using all identified significant determinants, we propose an integrative multidimensional model (see Figure 2.1) that incorporates the *internal* dimensions (i.e., *Salesperson* and *Organizational* determinants) and *external* dimensions (i.e., *Customer* and *Environmental* determinants) of B2B sales success. The model entitled "***A Multidimensional B2B Sales Success Model***" shows each dimension of B2B sales success and its related determinants. As can be seen in Figure 2.1, the closer the determinant is to the core of the circle, the more important and significant its effect is on B2B sales success. Additionally, Table 2.5 shows each determinant, the group rank (i.e., rank the determinants has in the group) and overall rank (i.e., rank the determinants has amongst all 31 determinants). Table 2.5 also shows the effects of moderators (i.e., "+": Positive Moderator; "-":

Negative Moderator) for each determinant, and the research evidence (i.e., number of studies) currently available for that determinant. Each component of our integrative model is discussed below.

Figure 2.1 Appears here

Table 2.5 appears here

2.5.2. Salesperson Determinants of B2B Sales Success

We operationalize our model's salesperson determinants using the competence typology proposed by Le Deist and Winterton (2005) for we believe it carries the potential to explain B2B success at the salesperson's level. Le Deist and Winterton (2005) typology focuses on 'core competence' which is described by Spencer and Spencer (1993, p. 4) as *"motives, traits, self-concepts, attitudes or values, content knowledge, or cognitive or behavioral skills – any individual characteristics that can be measured or counted reliably and that can be shown to differentiate significantly between superior and average performers, or between effective and ineffective performers".* The competence typology includes four dimensions: 1) *Cognitive Competence* (i.e., Professional Conceptual); 2) *Functional Competence* (i.e., Professional Operational); 3) *Social Competence* (i.e., Personal Operational); and 4) *Meta Competence* (i.e., Personal Conceptual)**.**

The authors of this paper together with an expert panel of B2B sales practitioners independently assigned each of the salesperson's determinants of sales success to a competency dimension. For most of the cases, we agreed on the resulting categorizations. Disagreements regarding the categorization were resolved through numerous discussions involving the authors and practitioners. As can be seen in Figure 2.1, the salesperson determinants were unevenly distributed across the four dimensions, which are discussed below.

Salesperson Cognitive Competence: Cognitive competence comprises a salesperson's knowledge and skill elements which are learned experientially (i.e., through study and practice) that may be used in the sales function as well as transversally. Our findings suggest that a cognitively competent salesperson is highly technical and experienced with product/service applications and specifications, customer use circumstances and preferences, and is aware of the industry's market situation. Effective technical skills allow salespeople to handle different product/service needs more effectively because they are knowledgeable with their product/service and understand customer needs and expectations related to the product/service (Rapp et al., 2012). Verbeke et al. (2011) meta-analytic study found selling-related knowledge (i.e., technical skills) to be significantly correlated with sales success at the salesperson's level. Technical skills have also been suggested to account for up to half the salesperson's success variance (Sharma et al., 2007). In retrospect, our meta-analysis revealed that experience had the second lowest positive correlation with sales success. We believe this is because our study only analyzes linear effects, and determinants such as experience may have a curvilinear (i.e., non-linear) effect on sales success. Hence, we call on future research to investigate curvilinear effects of sales success determinants. Nonetheless, the reality is that salespeople learn from the outcomes of different sales situations they encounter, and accordingly, they recollect prior sales encounters and implement the best strategies that are most likely to lead to a sale in the future (Giacobbe et al., 2006).

To sum up, a salesperson with high levels of cognitive competence must know *how* a product or service will offer solutions to a customer, know *why* a product or service is needed, and know *who* needs the product or service (Verbeke et al., 2011). The ability to master these three elements (*know-how*, *know-why* and *know-who*) is usually guided by a salesperson's repeated practices over time. As salespeople gain more experience, their knowledge of various selling situations, customer types, and selling strategies (Giacobbe et al., 2006) will eventually improve sales outcomes.

Salesperson Functional Competence: Functional competence includes learned skills that a salesperson should be able to demonstrate when selling. Practically, a B2B salesperson must be able to demonstrate some level of customer orientation (i.e., understand and meet customer needs and interests), salesmanship (i.e., identify prospects, qualify prospects and present product/service offerings to customers), and job effort (i.e., work certain hours, and make sales calls). Customer orientation is one of the most widely accepted concepts in the sales literature that is vital to the success of salespeople (Kidwell et al., 2007). Prior studies found that customer orientation significantly correlates with sales success (Franke & Park, 2006; Goad & Jaramillo, 2014; Zablah et al., 2012). Our informal tallying also identified customer orientation as the second most important salesperson determinant of sales success and the third one overall. Customer orientation is a cornerstone upon which customer trust, customer satisfaction, long-term salesperson-customer relationship, and sales success are realized (Wachner et al., 2009).

Similarly, our findings indicate that the higher the *effort* salespeople dedicate to their selling activities, the higher the level of sales success they will achieve. Effort in B2B sales has been conceptualized using salespeople's persistence in converting leads from prospects to customers (e.g., Carter et al., 2014), number of hours per week (e.g., Gablera et al., 2014), and call productivity (i.e., number of calls made over duration of time worked) (e.g., Ahearne et al., 2007). Most importantly, we found that the empirical literature lacks a consensus on the association between effort and sales success. For instance, Sager and Johnston (1989), Hunter and Perreault Jr. (2007), Carter et al. (2014) and (Ohiomah et al., 2019) found non-significant correlations between effort and sales success. Note that these four studies were conducted in different organizational settings and thus, there is a need for further research to look at other possible moderator variables such as location (e.g., North America vs. Asia) or output (e.g., Relationship quality and Traditional outputs).

Salesmanship skills represent another aspect of a functionally competent salesperson. Our meta-analysis revealed that salesmanship skills had the highest correlation with sales success (i.e., ranked # 1 in the salesperson determinant group, and ranked #2 overall), with individual studies' correlation ranging from 0.32 to 0.60. Salespeople represent the key link between organizations and their customers (Singh & Venugopal, 2015), and they are vital to identifying target customers and conveying an organization's message to them. One might argue that if salespeople fail at their task, the sales organization will likely fail. Salespeople who are highly skilled at focusing their acquisition efforts on qualified and ready to buy prospects, demonstrating organizational products/service value effectively, handling customer objections and questions, and closing sales will achieve high levels of sales success (Johlke, 2006; Wachner et al., 2009).

Salesperson Social Competence: Social competence comprises salespeople's inherent attitudes and behaviors that shape selling relationships with customers, to understand customer tensions and communicate with customers in a rational and conscientious way, including developing social responsibility and oneness with organizational goals and values (Winterton et al., 2006). The most investigated social competence determinants in the B2B sales literature include adaptive selling, salesperson commitment, interpersonal skills, job satisfaction, and motivation.

Interpersonal skills, a key salesperson's social competence trait, are important for improving success and developing long-term relationships with customers (Agnihotri & Krush, 2015; Plouffe et al., 2009). Interpersonal skills cover a salespersons' communication abilities, aptitudes to listen to customer comments, complaints, and feedback (Johlke, 2006), as well as abilities to empathize with customers' concerns and perceptions.

Another social competence determinant is adaptive selling, which has grown in importance since the 1980s (Weitz et al., 1986) as one of the key determinants of sales success (Giacobbe et al., 2006; Verbeke et al., 2011). Our informal tallying of significance ranks adaptive selling as the leading determinant of sales success at the salesperson's level. Our meta-analysis further confirms that highly adaptive salespeople will achieve higher levels of sales success, and as the moderating analysis showed, this determinant is significantly correlated across all moderating conditions. When selling adaptively, salespeople have to tailor sales messages to fit customer needs and preferences based on information that the salesperson perceives from the customer, thus enhancing strong buyer–seller relationships and trust bond with customers (Chakrabarty et al., 2013; Jaramillo et al., 2007; Kadic-Maglajlic et al., 2016).

Socially competent salespeople are also committed to their job and their organization. Committed salespeople become congruent with their organization's core values and will likely devote more time and energy towards completing their selling task and contribute strongly to the organization's collective goals (Ahearne et al., 2013; DeConinck & Johnson, 2009; Gablera et al., 2014; Mallin et al., 2017; Vilela et al., 2008). Committed salespeople will exert more effort towards serving organizational interests and will thus experience higher levels of sales success through improved selling behavior, selling effort and job satisfaction levels (Schwepker, 2013).

A socially competent salesperson will demonstrate high levels of job satisfaction. Our meta-analysis revealed that job satisfaction was strongly associated with sales success. Job satisfaction improves job-related skills, behaviors and strategies, which are key determinants of sales success (Franke & Park, 2006).

Another important aspect of a salesperson's social competence is his/her motivation *(intrinsic and extrinsic).* The sales literature confirms a positive link between a salesperson's motivation and sales success, particularly its influence on a salesperson's persona (e.g., Jaramillo et al., 2007). Churchill et al.'s (1985) meta-analysis found motivation to be the third most effective predictor of sales performance. Our meta-analysis indicates that salespeople who are both intrinsically and extrinsically motivated will experience a high degree of sales success.

Salesperson Meta-competence: Meta-competence includes inherent salesperson cognitive abilities related to coping with the uncertainty of the selling task, as well as the processes of learning and reflection of their selling skills' strength and weakness, behavior and knowledge. One of the fundamental physiognomies of salesperson learning and reflection is the salesperson's *age*. Our findings suggest that sales success increases slightly with age. In our study, age was the weakest and the only demographic determinant that was significantly correlated with sales success. Similar arguments that support the influence of sales experience on sales success can be made about a salesperson's age. A senior salesperson is likely to have gained experience overtime, thus will be in a better position to engage in profitable sales interactions. The senior salesperson would have carried out varying levels of complex sales interactions and will have improved technical, salesmanship, interpersonal, and behavioral approaches for each interaction. The senior salesperson may also have built a lasting relationship with existing customers, thus will experience improved cross-selling and up-selling opportunities and outcomes. Nonetheless, these arguments are only viable if the salesperson has been growing within the sales profession.

A meta-competent salesperson is also goal-oriented. A goal-oriented salesperson will pursue the acquisition and mastering of new skills, strategies and experiences, put more effort while facing difficult challenges or failure, and perform well for extrinsic values associated with the selling task (Silver et al., 2006).

An important characteristic of meta-competent salespeople is their role ambiguity. Consistent with the findings of Churchill et al. (1985) and Verbeke et al. (2011), our findings indicate that when salespeople lack clarity about their job demands, job expectations and job values, they will fail to achieve high levels of sales success. In our analysis, this was the only determinant that had a negative, but significant relationship with sales success ($r=0.23$, $p<0.001$). This makes sense because uncertainty of job requirements promotes negative consequences for salespeople who will, over time, exert less effort in their job (Behrman & Perreault, 1984; Zablah et al., 2012), experience unsatisfying job conditions (Miao & Evans, 2012), have inadequate knowledge to perform their job (Dubinsky & Hartley, 1986; Miao & Evans, 2013), and are not likely to engage in optimal and strategic selling behaviors (Roman & Iacobucci, 2010), which will lower sales success (Miao & Evans, 2012; Miao et al., 2007; Roman & Iacobucci, 2010).

Finally, a meta-competent salesperson believes in his/her ability to perform sales tasks, as well as his/her use of technology in successfully completing sales tasks. As our study suggests, a salesperson with high self-efficacy levels is better motivated, and will put in more effort to understand, prioritize, and meet customer expectations, which will result in better customer relationships and high sales success levels (Mullins et al., 2014; Schmitz & Ganesan, 2014; Yang et al., 2011). Salespeople with high self-efficacy levels are confident when engaging in selling tasks and will modify strategies to improve sales outcomes in varying sales situations (Kidwell et al., 2011; Román & Rodríguez, 2015; Yang et al., 2011).

To summarize the salesperson competence discussion, the results of this study indicate that salesperson skill determinants exhibited the highest influence on sales success (Figure 2.1). Thus, optimal sales success will come from confident, committed and motivated salespeople who combine and apply strong technical, interpersonal and salesmanship skills while practicing important selling behaviors and strategies (e.g., customer orientation and adaptive selling) during sales interactions. Competent salespeople devote more resources, effort, and attention to meet customer expectations, which builds a strong and lasting bond with customers and increase sales success.

2.5.3. Organizational Determinants of B2B Sales Success

The organizational dimension of our model consists of determinants related to organizational practices aimed at setting sales personnel's goals and objectives, guiding product and service portfolio strategies, and implementing mechanisms that enable salespeople to achieve sales goals and objectives. In previous studies, these determinants have often been discussed collectively as one determinant (e.g., internal environment, organizational/environmental factor) (Churchill et al., 1985; Verbeke et al., 2011). These determinants have a varying influence on a salesperson's competence structures and sales success.

Control systems are key organizational determinants that offer sales managers tools to influence procedures and activities to monitor, evaluate, and reward salespeople (Anderson & Oliver, 1987). Control systems are key drivers of salespeople's skills, motivation, effort and self-efficacy (Miao & Evans, 2012; Miao & Evans, 2013). Our findings suggest that activity, capability, and outcome control are all significant determinants of B2B sales success.

Another key sales success determinant for organizations is their deployed sales technology. This includes Information and Communication Technologies (Geyskens et al.) that can help the sales organization to conduct its essential activities (Hunter & Perreault Jr, 2006). Our findings suggest that the use and integration of ICT in the execution of routine sales tasks is likely to result in superior sales success. Ease of access to information, improved salesmanship and technical skills, as well as coordination have all been associated with ICT usage (Park et al., 2010; Rodriguez & Honeycutt, 2011; Román & Rodríguez, 2015). In addition, we believe that social media plays a crucial role in understanding the needs and preferences of potential customers, and serves as a medium for sharing important information and knowledge with customers, which can influence customer satisfaction and ultimately sales success (Agnihotri et al., 2016).

Furthermore**,** providing high levels of support creates an environment for salespeople to focus on achieving organizational goals and fulfilling customer needs. Our findings suggest that organizations that support salespeople with adequate resources will improve their sales success. In addition to effective support, training appears to be important for increasing salespeople's competencies and helping to close the gap for inexperienced salespeople (Abdolvand & Farzaneh, 2013). Effective training helps to transmit the necessary knowledge, selling skills, and experience that can help salespeople exhibit better problem-solving capabilities, communicate and deal with customers and integrate into the organizational culture.

Moreover, good leadership enables sales managers and supervisors to be closely engaged with their salespeople and motivate them to perform by clarifying expectations and core values, creating and articulating the organization's vision and providing feedback (Panagopoulos & Avlonitis, 2010; Schwepker Jr et al., 2010). Similarly, we found supervisee trust to be positively related to success. This is because a salesperson-supervisor relationship built on trust will provide an affirmation of equity and fairness of rewards for the salesperson who will, in turn, be highly committed, satisfied and productive (Agnihotri & Krush, 2015; Atuahene-Gima & Li, 2002). Such a trusting relationship is necessary for successful salesperson-supervisor interactions (Pappas & Flaherty, 2008), and will foster better reception of and compliance with comments, feedback and goals set by the supervisor, which will lead to better job performance (Agnihotri & Krush, 2015).

Last but not least, we found that organizations that use multiple sales channels, implement a well-defined selling model for customer segments and use an effective customer prioritization approach for their salespeople to follow will achieve higher levels of success (Terho et al., 2015).

2.5.4. Customer Determinants of B2B Sales Success

This group of determinants includes customer characteristics that are important for buyer purchasing propensity, and ultimately sales success. Our analysis identified customer satisfaction, trust, and relationship as key determinants. Previous research suggests that customer satisfaction with a product/service offering, as well as satisfaction with the salesperson, will increase sales success (e.g., .Homburg et al., 2011; Rapp et al., 2006). Highly satisfied customers will develop a sense of loyalty to a salesperson, which will influence future interactions with that salesperson (Roman & Iacobucci, 2010), increase share-of-wallet from up-selling and cross-selling opportunities (Mullins et al., 2014), and ultimately improve sales success levels (Roman & Iacobucci, 2010).

Customer trust is also crucial to improving buyer-seller relationships and sales success (Sengupta et al., 2000). Customer trust had the highest correlation with sales success for both the customer group and overall in this study. Customer trust exists when the customer has confidence in the salesperson's reliability and integrity to deliver what was promised and that the salesperson will not take any actions to hurt the interests of the customer (Sengupta et al., 2000). When a customer develops trust in a salesperson, it influences their intention and anticipation of future sales interactions with the selling firm (Chakrabarty et al., 2014).

A key outcome of both customer satisfaction and trust is the quality of the salesperson-customer relationship. A meta-analysis by Palmatier et al. (2006) shows that salesperson-customer relationship quality has a significant impact on sales success. Our findings support this association. A well-established relationship between a salesperson and a customer will reduce buyer uncertainty (Hughes et al., 2013), improve salesperson productivity (Park & Deitz, 2006), increase customer willingness to provide referrals and communicate competitor intelligence (Hughes et al., 2013), and improve customer loyalty and organizational profitability (Park et al., 2010).

2.5.5. Environmental Determinants of B2B Sales Success

Environmental determinants such as competitor influence (Stan et al., 2012), market and technology dynamism (Wang & Miao, 2015) and industry (Banin et al., 2016) etc., have mostly served as control variables in the B2B sales literature. They have an impact on organizational innovation, strategy implementation and sales outcomes (Wang & Miao, 2015). Our findings indicate that organizations that operate in a highly dynamic market may achieve high levels of sales success if they continually implement innovations and strategy that are geared towards meeting customer expectations and ever-changing needs (Pullins et al., 2017; Singh & Koshy, 2010).

2.6.Research Contributions

The findings of this study carry important implications for both theory and practice. First, we believe that this is the first work to perform a more detailed review and meta-analysis of the literature on B2B sales success determinants. In doing so, we respond to calls for generalizations in sales and marketing research (Hanssens, 2018). Most importantly, our findings revealed a higher number (31) of sales success determinants than previous meta-analyses related to sales success (e.g., Churchill et al. (1985) and Verbeke et al. (2011)). We argue that the difference in the number of determinants exists because our study avoids ambiguous subcategorizations of determinants. Indeed, we adopted most determinants in their foundational form. For instance, Verbeke et al. (2011) interpersonal skill determinant consists of presentation and communication skills, however, Rentz et al. (2002) conceptualized a salesperson's skill as (1) interpersonal skills (e.g., communication proficiency); (2) salesmanship skills (e.g., sales presentation); and (3) technical skills (e.g., selling knowledge), while our study adopted them as three mutually exclusive determinants. Additionally, as reported in Table 2.4, we found that the influence of several determinants on sales success may be significantly moderated by both measurement methods and research contexts. In our study, we explored two sets of moderators (i.e., number of studies (Single vs Multiple), and sales function (Inside sales vs Outside sales) that were not considered by previous studies investigating sales success determinants. This provides further understanding of the situations under which several determinants can be more effective and sustainable for sales success.

Also, to the best of our knowledge, this is the first study to come up with a comprehensive sales success model that captures important determinants from all the key pillars of the B2B selling process (i.e., salesperson, organization, customer and environment). Indeed, the reality of contemporary B2B selling requires salesperson's competence and sales organization's operational and strategic practices to be aligned with the complex preferences and needs of customers. Previous meta-analytic studies have mostly explored success determinants for salespeople (e.g., Verbeke et al., 2011), and have often ignored the other pillars of the selling process. Our proposed model will contribute to a better understanding of what is critical for facilitating and achieving B2B sales success.

In addition, our study is the first to conceptualize salesperson success using the competence typology. Our findings suggest that sales success at the salesperson level is a function of his/her cognitive (i.e., technical skills and experience), functional (i.e., salesmanship skills, customer orientation and effort), social (i.e., interpersonal skills, adaptive selling, commitment, job satisfaction and motivation), and meta-competences (i.e., self-efficacy, goal orientation, age, and role ambiguity). This comprehensive view will serve as a descriptive tool that can help sales managers identify salespeople's skills, knowledge, personal traits, and behaviors needed to successfully complete a sales task. In addition, sales managers can integrate formal education, training and skill development initiatives vital to fulfilling the objectives of their salespeople. This also provides managers with a new job requirement scale for identifying suitable candidates when recruiting salespeople.

Finally, our findings underscore the importance of the basic issue that sales success is at the heart of applied sales management strategies and operational practices in sales organizations. However, we believe that to date, most studies have suggested one or two determinants (i.e., Internal Environment, Organizational variables) to represent organizational determinants of sales success (e.g., Churchill et al., 1985; Verbeke et al., 2011). Our findings show that sales success at the organizational level results from strategic customer engagement practices as well as technology implementation and usage practices that help salespeople execute their tasks. We also found that implementing procedures that guide, evaluate, and reward salespeople, good leadership and trust relationships, along with effective salesperson training and support practices will result in improved sales success.

2.7. Opportunities for Future Research in B2B Sales

Our findings can be a basis for future research, particularly in areas lacking enough investigations like the organizational, customer, and especially environmental dimensions of the model (see Figure 2.1).

There is also an opportunity to investigate other salesperson cognitive competence determinants. For instance, cognitive attitude was identified as a key determinant of salesperson performance (Verbeke et al., 2011), yet not much has been done to empirically validate the influence of cognitive attitude on B2B sales success.

Our study also identified opportunities for research on salesperson functional competence. First, sales planning is an important aspect of the B2B selling process, yet not much research has been dedicated to this topic. While sales planning might improve a salesperson's technical skills, it might reduce success because the time salespeople spend on planning is seen as wasted on non-selling activities. Second, our review suggests that selling to satisfy customer needs helps to retain customers whose business really matters to organizations. This practice is crucial for current day selling because of the importance of long-term relationships. It has been suggested that the practice of customer orientation means that organizations have to sacrifice immediate sales achievements in order to create long-term relationships (Wachner et al., 2009). However, an empirical justification of this suggestion is lacking in the literature. Accordingly, we call on further research to empirically evaluate the short term and long-term implications of practicing customer orientation.

While a salesperson's social competence has received much attention, there are still areas that warrant further investigation. Although the influence of emotional intelligence has been validated in the literature (e.g., Kidwell et al., 2011), only a handful of studies have explored this relationship. Hence, we call for more research to further validate the impact of this concept. Second, our review confirmed that job satisfaction has been investigated as both a determinant of sales success (Franke and Park, 2006) and as a result of sales success (Yilmaz, 2002). Hence, we call on further review of the nature of the relationship between job satisfaction and sales success.

Our review revealed several research opportunities regarding organizational determinants of sales success. Future research should include the direct examination of possible moderators of firm size, firm age, product complexity, etc. We also suggest more research on the significance of team selling and inter-function coordination and communication on sales success. Even though the positive influence of these concepts on sales success has been validated in the literature (e.g., Rapp et al., 2012; Steward et al., 2010), the number of empirical justifications is limited. Furthermore, despite recent interest in social media, we found that social media usage has a small but significant correlation with sales success ($r = 0.19$, $p <0.001$). Thus, we join the likes of Verbeke et al. (2011) and Rodriguez et al. (2012) who call on future research to look into social media and networks and the role they will play in improving sales success. In addition, even though we observed a recent research interest in organizational sales strategy implementation and its impact on sales success (e.g., Terho et al., 2015), there is still much to be investigated there. Particularly, there is a need to understand the blend between an organizational-wide sales strategy and salesperson strategy, or whether the implementation of a particular organization-wide strategy interferes with the implementation of a salesperson strategy, because the reality is that salespeople are the key implementers of an organization's sales strategy at the customer-facing level. For instance, an organization's sales strategy may focus on a customer group that will have a long-term customer value which may include fewer customers and a long sales cycle. However, salespeople may seek to implement a hands-on selling strategy that will convert more customers with short-term value with a shorter sales cycle, so they can achieve their quota. How will this mismatch affect sales success? How should a salesperson's strategy be infused into an organization-wide strategy for optimum sales success? We also suggest more research on the interaction between organizational sales strategies and environmental determinants, such as market dynamism and competition intensity.

As for the customer and environmental determinants of sales success, we identified several concepts that influence the purchase intentions of customers. Future research should include the direct examination of moderators such as customer revenue, company size, lead quality, decision authority, market growth, timeframe, etc. These factors can determine customer purchase decisions which will ultimately result in varying sales success levels (Monat, 2011).

2.8. Conclusion and Limitations

Marketing and sales academics and practitioners are looking for meaningful and actionable research outcomes that can provide insights on how to improve their success (Pullins et al., 2017; Singh & Koshy, 2010), particularly in the context of B2B sales (Steward et al., 2019). This study answers an important question: *What are the dimensions and determinants of B2B sales success?* Our analysis of 139 related journal articles revealed that success in B2B sales is impacted by 31 determinants. We incorporated these determinants into a multidimensional model (see Figure 2.1) that provides a full picture of B2B sales success.

While this study makes several significant contributions, it has limitations that suggest directions for further research. The first limitation is the relatively small number of studies for some of the determinant relationships included in our meta-analysis because of the group of journal articles that were applicable to our research. Although scholars suggest that a meta-analysis can be performed with as few as two studies (Hunter & Schmidt, 1990), we preferred to have effect sizes from a higher number of studies to improve cumulative stability. Our data sample did not allow us to search and evaluate moderators for some determinant relationships. As we noted earlier, the number of related studies is growing, therefore, additional meta-analytic review work may be needed in the future. The second limitation is that regardless of our attempt to create a comprehensive dataset of relevant literature, there is a possibility that some eligible studies were not included in our analysis. The third limitation is that our meta-analysis is based on a bivariate analysis only, hence our findings are based on a linear effect. We suggest further research to consider performing a multivariate analysis to get more insights into linear and curved effects of possible ascendants, mediators, and direct sales success determinants. The current study uses the informal tally of significance and outcome of research models of the selected studies to guide our discussion and suggestions.

Table 2.1: Definition of Determinants

Determinants	Relationship Direction	Definitions	Example Variables
Salesperson Determinants			
Adaptive Selling	+	*"The altering of selling behaviours during a customer interaction or across customer interactions based on perceived information about the nature of the selling situation" (Weitz et al., 1986, p. 175)*	– Working Smart
Commitment		Include factors that leads individuals to strive toward organizational goals (Hunter & Thatcher, 2007)	
Job Commitment	+	*"The willingness to exert effort toward helping the organization achieve its goals and a strong desire to maintain membership in the organization"* (Chonko, Howell, & Bellenger, 1986)	– Job embeddedness – Job Involvement
Organizational Commitment	+	*"Refers to Individual's identification with the values and goals of the organization and loyalty to the organization"* (Ingram, Lee, & Skinner, 1989)	– Organizational Identification – Organization Citizenship Behavior
Customer Orientation	+	*"The degree to which salespeople practice the marketing concept by trying to help their customers make purchase decisions that will satisfy customer needs" (Saxe & Weitz, 1982, p. 344)*	– Customer Orientation
Demographical factors	+/-	Physical characteristics of the salesperson that can influence performance outcomes.	– Age – Gender – Education
Effort	+	*"Persistence in terms of the length of time devoted to work and continuing to try in the face of failure" (Sujan, Weitz, & Kumar, 1994, p. 40)*	– Call Activity – Working Hard – Selling Persistency
Experience	+	*"The general sales experience, the amount of time spent working with the current company and the time spent in the current territory"* (Rapp et al., 2006, p. 282)	– Job Experience
Goal Orientation	+	"*Underlying goals that people pursue in achievement situations*" *(Sujan et al., 1994, p. 39)*	– Achievement orientation – Learning orientation – Performance orientation
Interpersonal Skills	+	*"The cognitive process of actively sensing, interpreting, evaluating, and responding to the verbal and nonverbal messages of present or potential customers"* (Castleberry & Shepherd, 1993, p. 36)	– Communication style – Empathy – Listening

Determinants	Relationship Direction	Definitions	Example Variables
Job Satisfaction	+	*"All characteristics of a job and the work environment which industrial salespersons' find rewarding, fulfilling and satisfying, of frustrating and unsatisfying"* (Churchill Jr, Ford, & Walker Jr, 1974, p. 255)	– Job Satisfaction
Motivation		The degree to which employees are willing to expend effort on the job (Dubinsky & Hartley, 1986).	
Intrinsic Motivation	+	*"Involves engaging in a job activity for the pleasure and satisfaction derived from it"* (Jaramillo et al., 2007, p. 60)	– Task Enjoyment – Challenge seeking
Extrinsic Motivation	+	*"Involves engaging in a job activity to gain some sort of recognition or seek compensation"* (Jaramillo et al., 2007, p. 60)	– Recognition seeking – Compensation seeking
Role Perception		Perceptions of job demands and expectations by role partners (Walker Jr, Churchill Jr, & Ford, 1977).	
Role Ambiguity	-	*"Reflects the degree of lack of information available to the salesperson to perform the job adequately and uncertainty about different role set members"* (Singh, 1998, p. 70)	– Role Ambiguity
Role Conflict	-	"*The degree of incongruity or incompatibility of expectations communicated to a role incumbent by role senders*" (Michaels, Day, & Joachimsthaler, 1987, p. 30)	– Role Conflict
Salesmanship Skills	+	A line of conversation that attempts to convince a lead, to initiate and or close a sale of the product or service, as well as to the ability to qualify or categorize prospects and customers to be contacted (Ohiomah, Benyoucef, & Andreev, 2016; Rentz et al., 2002)	– Presentation Skills – Closing skills – Handling objections & negotiations – Prospecting & Targeting Skills
Self-Efficacy	+	Self-efficacy is a salesperson's confidence in his or her ability to execute actions necessary to perform successfully with customers (Sujan et al., 1994)	– Technology Self-Efficacy – Efficacy expectation
Technical Skills	+	The degree of knowledge that salespeople need to size up sales situations, classify prospects, and select appropriate sales strategies for sales interactions (Plouffe et al., 2009; Rentz et al., 2002)	Selling Knowledge – Understanding Customer Needs
Organizational Determinants			
Control Systems		*"An organization's set of procedures for monitoring, directing, evaluating, and*	

Determinants	Relationship Direction	Definitions	Example Variables
		compensating its employee" (Anderson & Oliver, 1987, p. 76)	
Activity Control	+	Activity control refers to the specification of the activities a salesperson is expected to perform, as well mechanism to monitor and reward salespeople behavior towards these activities (Miao & Evans, 2013)	– Activity Control – Process Control
Capability Control	+	Capability control is designed to develop and reward salespeople's selling skills (Challagalla & Shervani, 1996)	– Capability Control – Behaviour Control
Outcome Control	+	Outcome control is designed to objectively measure outcomes and compensate the salesforce (Anderson & Oliver, 1987)	– Output control
Leadership	+	*"Influencing subordinates broadening and elevating followers' goals and providing them with confidence to perform beyond the expectations specified in the implicit or explicit exchange agreement" (Dvir, Eden, Avolio, & Shamir, 2002, p. 735)*	– Empowering Leadership – Servant Leadership – Transactional & Transformational Leadership
Organizational Support	+	Includes organizational support systems such as information systems, training, supervisor, co-worker, and facilities support, which attempt to reduce employee stress and enhance motivation, improve job satisfaction and provide employees with resources to better serve and satisfy customers (Stan, Evans, Arnold, & McAmis, 2012)	– Internal technology support – Supportive Work Environment – Supervisory Support
Sales Strategy	+	*"The extent to which a firm engages in a set of activities and decisions regarding the allocation of scarce sales resources (i.e., people, selling effort, money) to manage customer relationships on the basis of the value of each customer for the firm"* (Panagopoulos & Avlonitis, 2010, p. 48)	– Customer Segmentation & Prioritization – Selling models – Use of multiple sales channels
Sales Technology	+	Any information and/or communication technology employed by the sales organization to conduct its essential activities (Hunter & Perreault Jr, 2006)	– Technology Usage & Adoption – Social Media Usage & Adoption
Supervisory Trust	+	"*The degree to which the salesperson perceives the supervisor as benevolent and believes that the supervisor is genuinely interested in the salesperson's welfare and provides due care for his or her need" (Atuahene-Gima & Li, 2002, p. 63)*	– Trust in Manager – Trust in Organization
Training	+	It involves the systematic attempt to describe, explain and transfer "good selling	– Technology training

Determinants	Relationship Direction	Definitions	Example Variables
		practices” to salespeople (Leigh, 1987, p. 39)	– Training investment
Customer Determinants			
Customer Trust	+	*"Customer confidence in the quality and reliability of the services offered by the organization"* (Garbarino & Johnson, 1999, p. 73)	– Customer Trust
Customer Satisfaction	+	A customer's overall evaluation based on the total purchase and consumption experience with a good or service over time (Johnson & Fornell, 1991)	– Satisfaction with products – Satisfaction with salesperson
Relationship Quality	+	Strength of trust, satisfaction, and commitment in buyer-seller exchanges (Mullins et al., 2014)	– Customer Relationship – Relationship Perception
Environmental Determinants			
Competitor Influence	+	Competitive intensity refers to the degree to which a firm faces competition within its industry (Jaworski & Kohli, 1993).	– Competitive Pressure
Market Dynamism	+	Market turbulence refers the rate of change in the customers type and customer preferences (Slater & Olson, 2000)	– Market Turbulence

Table 2.2: Informal Tally of Significance for Determinants of B2B Sales Success

Salesperson Determinants	Direct Effects			Indirect Effects			Total Effects		Weight
	No. of Effects	No. of +	No. of -/NS	No. of Effects	No. of +	No. of -/NS	Total Effects	Total +	
Adaptive Selling	37	34	3	3	3	0	40	37	34.2
Commitment									
Job Commitment	6	5	1	3	3	0	9	8	7.1
Organizational Commitment	8	7	1	4	2	2	12	9	6.8
Customer Orientation	24	20	4	5	4	1	29	24	19.9
Demographic Factors									
Age	3	1	2	4	0	4	7	1	0.1
Education	2	2	0	1	1	0	3	3	3.0
Gender	3	2	1	1	0	1	4	2	1.0
Effort	19	18	1	0	0	0	19	18	17.1
Experience	11	7	4	7	4	3	18	11	6.7
Goal Orientation	11	9	2	7	7	0	18	16	14.2
Interpersonal Skills	8	3	5	4	4	0	12	7	4.1
Job Satisfaction	6	5	1	2	2	0	8	7	6.1
Motivation									
Extrinsic Motivation	6	2	4	2	2	0	8	4	2.0
Intrinsic Motivation	12	10	2	2	1	1	14	11	8.6
Role Perception									
Role Ambiguity	11	1	10	7	0	7	18	1	0.1
Role Conflict	7	2	5	4	2	2	11	4	1.5
Salesmanship Skills	26	20	6	1	0	1	27	20	14.8
Self-Efficacy	11	10	1	8	8	0	19	18	17.1
Technical Skills	15	11	4	3	3	0	18	14	10.9
Organizational Determinants	**Direct Effects**			**Indirect Effects**			**Total Effects**		**Weight**
	No. of Effects	**No. of +**	**No. of -/NS**	**No. of Effects**	**No. of +**	**No. of -/NS**	**Total Effects**	**Total +**	
Control Systems									
Activity	0	0	0	7	5	2	7	5	3.6
Capability	3	3	0	5	5	0	8	8	8.0
Outcome	2	2	0	5	2	3	7	4	2.3
Leadership	5	4	1	12	8	4	17	12	8.5
Organizational Support	7	4	3	7	6	1	14	10	7.1
Sales Strategy	8	7	1	2	2	0	10	9	8.1
Sales Technology									
Technology Usage	15	15	0	5	5	0	20	20	20.0
Social Media Usage	2	2	0	5	5	0	7	7	7.0
Supervisory Trust	4	3	1	4	3	1	8	6	4.5
Training	5	4	1	8	5	3	13	9	6.2

Customer & Prospects Determinants	Direct Effects			Indirect Effects			Total Effects		Weight
	No. of Effects	No. of +	No. of -/NS	No. of Effects	No. of +	No. of -/NS	Total Effects	Total +	
Customer Satisfaction	2	2	0	0	0	0	2	2	2
Customer Trust	3	3	0	1	1	0	4	4	4
Lead Complexity	1	0	1	5	4	1	6	4	2.7
Relationship Quality	6	6	0	2	2	0	8	8	8
Environment Variables	**Direct**			**Indirect**			**Total Effects**		**Weight**
	No. of Effects	**No. of +**	**No. of -/NS**	**No. of Effects**	**No. of +**	**No. of -/NS**	**Total Effects**	**Total +**	
Competitor Influence	5	1	4	3	2	1	8	3	1.1
Market & Technology Dynamism	2	1	1	4	4	0	6	5	4.2

No. of +: Number of studies with positive significant relationship

No. of -/NS: Number of studies with negative and non-significant relationshi

Table 2.3: Correlation Results for Determinants of B2B Sales Success

Salesperson Determinants	No. of Effects	Total Sample	Mean r	Reliability Sample-weighted mean r	CI		Z	Q-Stat	Fail-n
					CI-	CI+			
Adaptive Selling	40	8545	0.33	0.34*	0.30	0.38	14.43	213.58	2662
Commitment									
Job Commitment	7	1968	0.16	0.17***	0.01	0.32	2.56	50.92	9
Organizational Commitment	10	2943	0.24	0.25*	0.14	0.36	5.09	79.49	66
Customer Orientation	28	7713	0.28	0.28*	0.23	0.33	10.51	133.63	1248
Demographic Factors									
Age	13	3361	0.10	0.10***	0.01	0.18	2.52	69.55	14
Gender	9	2454	-0.05	-0.04ns	-0.09	0.00	-2.47	6.23	8
Education	8	2570	0.00	-0.01ns	-0.09	0.07	-0.33	18.02	0
Effort	21	4550	0.31	0.35*	0.19	0.49	4.32	419.14	198
Experience	33	9408	0.16	0.16*	0.12	0.21	7.67	182.98	476
Goal Orientation	9	1951	0.24	0.25*	0.14	0.36	4.97	41.01	67
Interpersonal Skills	8	1472	0.40	0.40*	0.30	0.50	8.71	23.45	220
Job Satisfaction	15	4009	0.20	0.24*	0.17	0.31	7.11	69.02	234
Motivation									
Extrinsic Motivation	7	1348	0.24	0.24*	0.11	0.35	4.61	21.97	48
Intrinsic Motivation	10	2310	0.29	0.29*	0.18	0.40	5.82	67.80	90
Role Perception									
Role Ambiguity	14	4557	-0.23	-0.23*	-0.31	-0.15	-5.93	76.70	198
Role Conflict	11	3445	-0.03	-0.03ns	-0.13	0.06	-0.85	48.50	0
Salesmanship Skills	17	3977	0.43	0.44*	0.36	0.51	10.69	112.80	728
Self-Efficacy	21	5127	0.36	0.39*	0.28	0.49	6.80	329.89	357
Technical Skills	19	5147	0.39	0.40*	0.31	0.48	8.60	169.77	579

Organizational Determinants	No. of Effects	Total Sample	Mean r	Reliability Sample-weighted mean r	CI		Z	Q-Stat	Fail-n
					CI-	CI+			
Control Systems									
Activity	8	2000	0.24	0.25*	0.11	0.37	4.32	51.87	363
Capability	12	2596	0.24	0.25*	0.15	0.34	5.40	74.32	92
Outcome	12	2824	0.22	0.23*	0.10	0.34	3.99	112.78	50
Leadership	12	3321	0.25	0.25*	0.11	0.39	3.79	127.97	73
Organizational Support	10	2594	0.16	0.17*	0.08	0.25	4.39	29.778	59
Sales Strategy	4	2843	0.24	0.26*	0.13	0.39	5.94	7.25	72
Supervisory Trust	9	2559	0.24	0.24*	0.13	0.35	4.90	49.40	72
Sales Technology									
Technology Usage	20	6050	0.25	0.25*	0.18	0.32	7.22	107.76	431
Social Media Use	6	2568	0.21	0.20*	0.16	0.24	11.94	3.74	180
Training	12	3380	0.22	0.23*	0.16	0.30	6.77	43.40	186

Customer & Prospects Determinants	No. of Effects	Total Sample	Mean r	Reliability Sample-weighted mean r	CI		Z	Q-Stat	Fail-n
					CI-	CI+			
Customer Trust	3	549	0.47	0.48*	-0.14	0.83	3.40	28.99	9
Customer Satisfaction	7	1438	0.32	0.33*	0.18	0.46	5.17	27.72	84
Relationship Quality	7	2101	0.29	0.31*	0.03	0.55	2.66	164.87	13
Lead Complexity	5	1138	0.19	0.20*	0.02	0.36	3.08	22.15	9

Environmental Determinants	No. of Effects	Total Sample	Mean r	Reliability Sample-weighted mean r	CI		Z	Q-Stat	Fail-n
					CI-	CI+			
Competitor Influence	9	2584	0.04	0.04ns	-0.04	0.12	1.11	29.502	0
Market & Technology Dynamism	7	1301	0.16	0.15*	0.08	0.23	4.77	8.0188	54

*p = <.001; **p = <.01; ***p = <.05; ns = Statistical non-significant relationships

Table 2.4: Results of the Moderator Analysis

Salesperson Determinants	Measure Source		Measure Item	Research Context	Industry	Business Function
	Self (0) vs Manager (1)	Subjective (0) vs Objective (1)	Single (0) vs Multiple (1)	Goods (0) Vs Services (1)	Single (0) Vs Multiple (1)	Outside (0) Vs Inside (1)
Adaptive Selling	na	ns	na	-0.34 *	0.09 ns	-0.18 **
Commitment						
Job Commitment	na	0.60 *	0.64 *	-0.73 *	0.82 *	0.72 *
Organizational Commitment	na	na	na	na	0.02 ns	na
Customer Orientation	na	0.14 ns	na	-0.44 *	0.46*	0.08 ns
Demographic Factors						
Age	na	0.12 ns	na	-0.24**	0.38 *	-0.39 *
Gender	0.01 ns	-0.07 ns	na	0.02 ns	na	-0.32 ns
Education	na	0.38 ns	na	na	-0.02 ns	na
Effort	na	-0.42 *	na	0.15 *	0.21 *	-0.24 *
Experience	na	-0.42 *	na	na	0.12 ns	na
Goal Orientation	0.02 ns	0.03 ns	na	0.26 ns	-0.64 *	-0.26 ns
Interpersonal Skills	na	na	na	na	na	0.21 ns
Job Satisfaction	na	na	na	0.44 *	-0.59 *	na
Motivation						
Extrinsic Motivation	na	-0.07 ns	na	na	0.50 **	0.20 ns
Intrinsic Motivation	na	0.32 *	na	na	-0.13 ns	na
Role Ambiguity	na	na	na	0.14 ns	na	-0.34 *
Salesmanship Skills	na	-0.01 ns	na	na	0.45 *	0.41 *
Self-Efficacy	na	-0.31 *	0.39 *	-0.03 ns	-0.02 ns	-0.38 *
Technical Skills	-0.23 **	-0.20 *	na	na	-0.43 *	-0.27 *
Organizational Determinants	**Measure Source**		**Measure Item**	**Research Context**	**Industry**	**Business Function**
	Self (0) vs Manager (1)	**Subjective (0) vs Objective (1)**	**Single (0) vs Multiple (1)**	**Goods (0) Vs Services (1)**	**Single (1) Vs Multiple (1)**	**Outside (0) Vs Inside (1)**
Control Systems						
Activity	na	-0.72 *	na	na	na	0.34 *

Capability	na	-0.12 ns	na	na	-0.02 ns	na
Outcome	na	na	-0.66 *	na	0.04 ns	na
Leadership	na	-0.48 *	na	na	0.24 *	na
Organizational Support	na	0.31 ns	na	-0.39 **	0.68 *	0.67 *
Supervisory Trust	-0.29 ns	-0.33 **	na	-0.26 ns	0.26 ns	-0.61 *
Sales Technology						
Technology Usage	na	-0.56 *	0.52 *	na	0.53 *	0.53 *
Social Media Use	-0.41 ns	-0.41 ns	na	na	na	na
Training	na	na	na	na	0.61 *	0.24 ns
Customer & Prospects Determinants	**Measure Source**		**Measure Item**	**Research Context**	**Industry**	**Business Function**
	Self (0) vs Manager (1)	**Subjective (0) vs Objective (1)**	**Single (0) vs Multiple (1)**	**Goods (0) Vs Services (1)**	**Single (1) Vs Multiple (1)**	**Outside (0) Vs Inside (1)**
Customer Satisfaction	na	na	-0.14 ns	na	na	0.38**
Relationship Quality	na	na	na	na	na	0.73 *
Environmental Determinants	**Measure Source**		**Measure Item**	**Research Context**	**Industry**	**Business Function**
	Self (0) vs Manager (1)	**Subjective (0) vs Objective (1)**	**Single (0) vs Multiple (1)**	**Goods (0) Vs Services (1)**	**Single (1) Vs Multiple (1)**	**Outside (0) Vs Inside (1)**
Competitor Influence	na	na	na	-0.27 ns	0.22 ns	na
Market & Technology Dynamism	0.93 *	0.72 **	na	na	0.31 ns	na

*p: = <.001; **p = <.01; ***p = <.05
na = Insufficient variation in this group or to permit meaningful moderator analysis
ns = Statistical non-significant relationships
r = Adjusted correlation for the moderator sub-group labelled “1” (e.g., Manager (1))

Table 2.5: Summary of findings

Salesperson Determinants	Group Rank (Overall Rank)	Importance	Moderators							Research Evidence
			Manager Evaluation	Objective Measure	Multiple Industries	Selling Services	Multiple Measures	Inside Selling	Last Decade	
Cognitive Competence										
Technical Skills	3 (**4**)	High		-			-	-	-	★★
Experience	15 (**29**)	Medium		-					+	★★★
Functional Competence										
Salesmanship Skills	1 (**2**)	High					+	+		★★
Effort	5 (**6**)	High		-		+	+	-	-	★★★
Customer Orientation	8 (**11**)	Medium				-	+			★★★
Social Competence										
Interpersonal Skills	2 (**3**)	High								★
Adaptive Selling	6 (**7**)	High				-		-		★★★
Intrinsic Motivation	7 (**10**)	Medium		+					+	★★
Organizational Commitment	9 (**14**)	Medium								★★
Job Satisfaction	11 (**20**)	Medium				+	-		+	★★
Extrinsic Motivation	12 (**21**)	Medium					+			★
Job Commitment	14 (**27**)	Low		+	+	-	+	+		★
Meta Competence										
Self-Efficacy	4 (**5**)	High		-	+			-		★★★
Goal Orientation	10 (**15**)	Medium					-			★
Role Ambiguity	13 (**23**)	Medium						-	-	★★
Age	16 (**31**)	Low				-	+	-		★★
Organizational Determinants	**Group Rank**	**Importance**	**Moderators**							**Research Evidence**
			Manager Evaluation	**Objective Measure**	**Multiple Industries**	**Selling Services**	**Multiple Measures**	**Inside Selling**	**Last Decade**	
Sales Strategy	1 (**12**)	Medium								★
Leadership	2 (**13**)	Medium		-			+			★★

Capability Control	3 (**16**)	Medium								★★
Technology Usage	4 (**17**)	Medium		-	+		+	+		★★★
Activity Control	5 (**18**)	Medium		-				+		★
Supervisory Trust	6 (**19**)	Medium		-				-		★
Training	7 (**22**)	Medium					+		+	★★
Outcome	8 (**24**)	Medium			-				+	★★
Social Media Use	9 (**25**)	Medium								★
Organizational Support	10 (**28**)	Low				-	+	+	-	★
Customer & Prospects Determinants	**Group Rank**	**Importance**	**Moderators**							**Research Evidence**
			Manager Evaluation	**Objective Measure**	**Multiple Industries**	**Selling Services**	**Multiple Measures**	**Inside Selling**	**Last Decade**	
Customer Trust	1 (**1**)	High								★
Customer Satisfaction	2 (**8**)	High						+		★
Relationship Quality	3 (**9**)	Medium						+	-	★
Lead Complexity	4 (**26**)	Low								★
Environmental Determinants	**Group Rank**	**Importance**	**Moderators**							**Research Evidence**
			Manager Evaluation	**Objective Measure**	**Multiple Industries**	**Selling Services**	**Multiple Measures**	**Inside Selling**	**Last Decade**	
Market & Technology Dynamism	NA (**30**)	Low	+	+						★

★ = Less than 10 Studies; ★★ = 10 to 19 Studies; ★★★ = 20 or more
"+" = Positive Moderator; "-" = Negative Moderator

Figure 2.1: An Integrative B2B Sales Success Model

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*, 2661-2670.

Agnihotri, R., Dingus, R., Hu, M. Y., & Krush, M. T. (2016). Social media: Influencing customer satisfaction in B2B sales. *Industrial Marketing Management, 53*, 172-180.

Agnihotri, R., & Krush, M. T. (2015). Salesperson empathy, ethical behaviors, and sales performance: The moderating role of trust in one's manager. *Journal of Personal Selling and Sales Management, 35*, 164-174. doi:10.1080/08853134.2015.1010541

Ahearne, M., Haumann, T., Kraus, F., & Wieseke, J. (2013). It's a matter of congruence: How interpersonal identification between sales managers and salespersons shapes sales success. *Journal of the Academy of Marketing Science, 41*, 625-648.

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*, 336-349. doi:10.1016/j.ijresmar.2007.09.003

Anderson, E., & Oliver, R. L. (1987). Perspectives on behavior-based versus outcome-based salesforce control systems. *The Journal of marketing*, 76-88.

Anderson, E. W., Fornell, C., & Rust, R. T. (1997). Customer satisfaction, productivity, and profitability: Differences between goods and services. *Marketing Science, 16*(2), 129-145.

Atuahene-Gima, K., & Li, H. (2002). When does trust matter? Antecedents and contingent effects of supervisee trust on performance in selling new products in China and the United States. *Journal of Marketing, 66*, 61-81.

Banin, A. Y., Boso, N., Hultman, M., Souchon, A. L., Hughes, P., & Nemkova, E. (2016). Salesperson improvisation: Antecedents, performance outcomes, and boundary conditions. *Industrial Marketing Management, 59*, 120-130. doi:10.1016/j.indmarman.2016.02.007

Bax, L. (2017). MIX2. 0—Professional software for meta-analysis in Excel. Version 2.0. 1.6. BiostatXL, 2017. In.

Behrman, D. N., & Perreault, W. D. (1982). Measuring the performance of industrial salespersons. *Journal of Business Research, 10*, 355-370. doi:10.1016/0148-2963(82)90039-X

Behrman, D. N., & Perreault, W. D. (1984). A Role Stress Model of the Performance and Satisfaction of Industrial Salespersons. *Journal of marketing, 48*, 9-21.

Card, N. A. (2015). *Applied meta-analysis for social science research*: Guilford Publications.

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*, 91-111.

Chakrabarty, S., Brown, G., & Widing, R. (2013). Distinguishing between the roles of customer-oriented selling and adaptive selling in managing dysfunctional conflict in buyer-seller relationships. *Journal of Personal Selling and Sales Management, 33*, 245-260.

Chakrabarty, S., Widing II, R. E., & Brown, G. (2014). Selling behaviours and sales performance: The moderating and mediating effects of interpersonal mentalizing. *Journal of Personal Selling and Sales Management, 34*, 112-122. doi:10.1080/08853134.2014.890899

Churchill, G. A., Ford, N. M., Hartley, S. W., & Walker Jr, O. C. (1985). The Determinants of Salesperson Performance: A Meta-Analysis. *Journal of Marketing Research, 22*, 103-118.

Cohen, J. (1969). Statistical power analysis for the behavioural science. *New York: Academic Press*.

Crosno, J. L., & Dahlstrom, R. (2008). A meta-analytic review of opportunism in exchange relationships. *Journal of the Academy of Marketing Science, 36*(2), 191-201.

DeConinck, J. B., & Johnson, J. T. (2009). The effects of perceived supervisor support, perceived organizational support, and organizational justice on turnover among salespeople. *Journal of Personal Selling & Sales Management, 29*, 333-350.

Dubinsky, A. J., & Hartley, S. W. (1986). A Path-Analytic Study of a Model of Salesperson Performance. *Journal of the Academy of Marketing Science, 14*, 36.

Franke, G. R., & Park, J.-E. (2006). Salesperson adaptive selling behavior and customer orientation: A meta-analysis. *Journal of Marketing Research, 43*, 693-702. doi:10.1509/jmkr.43.4.693

Frino, M. G., & Desiderio, K. P. (2013). The Role of Demographics as Predictors of Successful Performance of Sales Professionals in Business-to-Business Sales Organizations. *Performance Improvement Quarterly, 25*(4), 7-21.

Gablera, C. B., Rappb, A., & Richeyb, R. G. (2014). The effect of environmental orientation on salesperson effort and participation: The moderating role of organizational identification. *Journal of Personal Selling and Sales Management, 34*, 173-187. doi:10.1080/08853134.2014.890906

Geyskens, I., Steenkamp, J.-B. E., & Kumar, N. (1998). Generalizations about trust in marketing channel relationships using meta-analysis. *International Journal of Research in Marketing, 15*(3), 223-248.

Giacobbe, R. W., Jackson Jr., D. W., 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*, 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*, 285-301. doi:10.1080/08853134.2014.899471

Hanssens, D. M. (2018). The value of empirical generalizations in marketing. In: Springer.

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.

Henard, D. H., & Szymanski, D. M. (2001). Why some new products are more successful than others. *Journal of Marketing Research, 38*(3), 362-375.

Herjanto, H., & Franklin, D. (2019). Investigating salesperson performance factors: A systematic review of the literature on the characteristics of effective salespersons. *Australasian Marketing Journal, 27*(2), 104-112. doi:10.1016/j.ausmj.2018.12.001

Homburg, C., Maller, M., & Klarmann, M. (2011). When Should the Customer Really Be King? On the Optimum Level of Salesperson Customer Orientation in Sales Encounters. *Journal of Marketing, 75*, 55-74.

Hughes, D. E., Le Bon, J., & Rapp, A. (2013). Gaining and leveraging customer-based competitive intelligence: the pivotal role of social capital and salesperson adaptive selling skills. *Academy of Marketing Science.Journal, 41*, 91-110.

Hunter, G. K., & Perreault Jr, W. D. (2006). Sales Technology Orientation, Information Effectiveness, and Sales Performance. *Journal of Personal Selling & Sales Management, 26*, 95-113.

Hunter, G. K., & Perreault Jr., W. D. (2007). Making sales technology effective. *Journal of Marketing, 71*, 16-34. doi:10.1509/jmkg.71.1.16

Hunter, J. E., & Schmidt, F. (1990). Dichotomization of continuous variables: The implications for meta-analysis. *Journal of Applied Psychology, 75*(3), 334.

Hunter, J. E., & Schmidt, F. L. (2004). *Methods of meta-analysis: Correcting error and bias in research findings*: Sage.

Jaramillo, F., Locander, W. B., Spector, P. E., & Harris, E. G. (2007). Getting the Job Done: The Moderating Role of Initiative on the Relationship Between Intrinsic Motivation and Adaptive Selling. *Journal of Personal Selling & Sales Management, 27*, 59-74.

Jaramillo, F., & Marshall, G. W. (2004). Critical success factors in the personal selling process: An empirical investigation of Ecuadorian salespeople in the banking industry. *International Journal of Bank Marketing, 22*, 9-25. doi:10.1108/02652320410514906

Johlke, M. C. (2006). Sales presentation skills and salesperson job performance. *Journal of Business and Industrial Marketing, 21*, 311-319. doi:10.1108/08858620610681614

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. doi:10.1108/JBIM-09-2015-0168

Ketchen Jr, D. J., Combs, J. G., Russell, C. J., Shook, C., Dean, M. A., Runge, J., . . . Baker, R. (1997). Organizational configurations and performance: A meta-analysis. *Academy of Management Journal, 40*(1), 223-240.

Kidwell, B., Hardesty, D. M., Murtha, B. R., & Sheng, S. (2011). Emotional Intelligence in Marketing Exchanges. *Journal of marketing, 75*, 78-95. doi:10.1509/jmkg.75.1.78

Kidwell, B., McFarland, R. G., & Avila, R. A. (2007). Perceiving emotion in the buyer-seller interchange: The moderated impact on performance. *Journal of Personal Selling and Sales Management, 27*, 119-132.

Kirca, A. H., Jayachandran, S., & Bearden, W. O. (2005). Market orientation: A meta-analytic review and assessment of its antecedents and impact on performance. *Journal of Marketing, 69*(2), 24-41.

Le Deist, F. D., & Winterton, J. (2005). What is competence? *Human resource development international, 8*(1), 27-46.

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. doi:10.1108/JBIM-03-2015-0048

Mallin, M. L., Gammoh, B. S., Bolman Pullins, E., & Johnson, C. M. (2017). A new perspective of salesperson motivation and salesforce outcomes: the mediating role of salesperson-brand identification. *Journal of marketing, 25*, 357-374. doi:10.1080/10696679.2017.1345597

Marshall, G. W., Moncrief, W. C., & Lassk, F. G. (1999). The current state of sales force activities. *Industrial Marketing Management, 28*(1), 87-98.

Miao, C. F., & Evans, K. R. (2012). Effects of formal sales control systems: A combinatory perspective. *International Journal of Research in Marketing, 29*, 181-191. doi:10.1016/j.ijresmar.2011.09.002

Miao, C. F., & Evans, K. R. (2013). The interactive effects of sales control systems on salesperson performance: a job demands-resources perspective. *Academy of Marketing Science.Journal, 41*, 73-90. doi:http://dx.doi.org/10.1007/s11747-012-0315-4

Miao, C. F., Evans, K. R., & Shaoming, Z. (2007). The role of salesperson motivation in sales control systems - Intrinsic and extrinsic motivation revisited. *Journal of Business Research, 60*, 417-425. doi:10.1016/j.jbusres.2006.12.005

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Annals of internal medicine, 151*(4), 264-269.

Monat, J. P. (2011). Industrial sales lead conversion modeling. *Marketing Intelligence & Planning, 29*(2), 178-194.

Mullins, R. R., Ahearne, M., Lam, S. K., Hall, Z. R., & Boichuk, J. P. (2014). Know your customer: How salesperson perceptions of customer relationship quality form and influence account profitability. *Journal of Marketing, 78*, 38-58.

Ohiomah, A., Andreev, P., Benyoucef, M., & Hood, D. (2019). The role of lead management systems in inside sales performance. *Journal of Business Research, 102*, 163-177. doi:10.1016/j.jbusres.2019.05.018

Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems, 37*.

Palmatier, R. W., Dant, R. P., Grewal, D., & Evans, K. R. (2006). Factors influencing the effectiveness of relationship marketing: A meta-analysis. *Journal of Marketing, 70*(4), 136-153.

Panagopoulos, N. G., & Avlonitis, G. J. (2010). Performance implications of sales strategy: The moderating effects of leadership and environment. *International Journal of Research in Marketing, 27*(1), 46-57.

Pappas, J. M., & Flaherty, K. E. (2008). The effect of trust on customer contact personnel strategic behavior and sales performance in a service environment. *Journal of Business Research, 61*, 894-902. doi:10.1016/j.jbusres.2007.09.017

Park, J. E., & Deitz, G. D. (2006). The effect of working relationship quality on salesperson performance and job satisfaction: Adaptive selling behavior in Korean automobile sales representatives. *Journal of Business Research, 59*, 204-213. doi:10.1016/j.jbusres.2005.04.002

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*, 1128-1138. doi:10.1016/j.indmarman.2009.11.003

Plank, R. E., & Greene, J. N. (1996). Personal construct psychology and personal selling performance. *European Journal of Marketing, 30*, 25-48.

Plouffe, C. R., Bolander, W., & Cote, J. A. (2014). Which influence tactics lead to sales performance? It is a matter of style. *Journal of Personal Selling & Sales Management, 34*, 141-159.

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*, 422-439. doi:10.1007/s11747-009-0142-4

Pullins, E. B., Timonen, H., Kaski, T., & Holopainen, M. (2017). An investigation of the theory practice gap in professional sales. *Journal of Marketing Theory Practice, 25*(1), 17-38.

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*, 279-293.

Rapp, A., Beitelspacher, L. S., Schillewaert, N., & Baker, T. L. (2012). The differing effects of technology on inside vs. outside sales forces to facilitate enhanced customer orientation and interfunctional coordination. *Journal of Business Research, 65*, 929-936. doi:10.1016/j.jbusres.2011.05.005

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.

Rodriguez, M., & Honeycutt, E. D. (2011). Customer Relationship Management (CRM)'s Impact on B to B Sales Professionals' Collaboration and Sales Performance. *Journal of Business-to-Business Marketing, 18*, 335-356. doi:10.1080/1051712X.2011.574252

Rodriguez, M., Peterson, R. M., & Krishnan, V. (2012). Social Media's Influence on Business-To-Business Sales Performance. *Journal of Personal Selling & Sales Management, 32*, 365-378.

Roman, 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*, 363-382.

Román, S., & Rodríguez, R. (2015). The influence of sales force technology use on outcome performance. *The Journal of Business & Industrial Marketing, 30*, 771-783.

Rosenthal, R. (1991). *Meta-analytic procedures for social research* (Vol. 6): Sage.

Rosenthal, R. (1995). Writing meta-analytic reviews. *Psychological bulletin, 118*(2), 183.

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*, 1850.

Sager, J. K., & Johnston, M. W. (1989). Antecedents and outcomes of organizational commitment: A study of salespeople. *Journal of Personal Selling and Sales Management, 9*, 30-41. doi:10.1080/08853134.1989.10754511

Schmitz, C., & Ganesan, S. (2014). Managing customer and organizational complexity in sales organizations. *Journal of Marketing, 78*, 59-77.

Schwepker, C. H. (2013). Improving Sales Performance Through Commitment to Superior Customer Value: The Role of Psychological Ethical Climate. *Journal of Personal Selling & Sales Management, 33*, 389-402. doi:10.2753/PSS0885-3134330403

Schwepker, C. H., & Good, D. J. (2011). Moral Judgment and its Impact on Business-to-Business Sales Performance and Customer Relationships. *Journal of Business Ethics, 98*, 609-625.

Schwepker Jr, C. H., Good, D. J., Schwepker, C. H., & Good, D. J. (2010). Transformational leadership and its impact on sales force moral judgment. *Journal of Personal Selling & Sales Management, 30*, 299-317. doi:10.2753/PSS0885-3134300401

Sengupta, S., Krapfel, R. E., & Pusateri, M. A. (2000). An empirical investigation of key account salesperson effectiveness. *The Journal of Personal Selling and Sales, 20*, 253-261. doi:10.1080/08853134.2000.10754245

Sharma, A., Levy, M., & Evanschitzky, H. (2007). The variance in sales performance explained by the knowledge structures of salespeople. *Journal of Personal Selling & Sales Management, 27*, 169-181.

Silver, L. S., Dwyer, S., & Alford, B. (2006). Learning and Performance Goal Orientation of Salespeople Revisited: The Role of Performance-Approach and Performance-Avoidance Orientations. *Journal of Personal Selling & Sales Management, 26*, 27-38.

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*, 594-607. doi:10.1108/JBIM-08-2012-0141

Spencer, L. M., & Spencer, S. M. (1993). *Competence at Work models for superior performance*: John Wiley & Sons.

Stan, S., Evans, K., Arnold, T., & McAmis, G. (2012). The Moderating influence of organizational support on the development of salesperson job performance: Can an organization provide too much support? *Journal of Personal Selling and Sales Management, 32*, 405-419. doi:10.2753/PSS0885-3134320401

Steward, M., Walker, B., Hutt, M., & Kumar, A. (2010). The coordination strategies of high-performing salespeople: internal working relationships that drive success. *Journal of the Academy of Marketing Science, 38*, 550-566.

Steward, M. D., Narus, J. A., Roehm, M. L., & Ritz, W. (2019). From transactions to journeys and beyond: The evolution of B2B buying process modeling. *Industrial Marketing Management*.

Sullivan, U. Y., Peterson, R. M., & Krishnan, V. (2012). Value creation and firm sales performance: The mediating roles of strategic account management and relationship perception. *Industrial Marketing Management, 41*, 166-173. doi:10.1016/j.indmarman.2011.11.019

Terho, H., Eggert, A., Haas, A., & Ulaga, W. (2015). How sales strategy translates into performance: The role of salesperson customer orientation and value-based selling. *Industrial Marketing Management, 45*, 12-21. doi:10.1016/j.indmarman.2015.02.017

Thaichon, P., Surachartkumtonkun, J., Quach, S., Weaven, S., & Palmatier, R. W. (2018). Hybrid sales structures in the age of e-commerce. *Journal of Personal Selling Sales Management*, 1-26.

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*, 407-428. doi:http://dx.doi.org/10.1007/s11747-010-0211-8

Vilela, B. B., Gonzalez, J. A. V., & Ferra-n, P. F. (2008). Person-organization fit, OCB and performance appraisal: Evidence from matched supervisor-salesperson data set in a Spanish context. *Industrial Marketing Management, 37*, 1005-1019. doi:10.1016/j.indmarman.2007.11.004

Wachner, T., Plouffe, C. R., & Grégoire, Y. (2009). SOCO's impact on individual sales performance: The integration of selling skills as a missing link. *Industrial Marketing Management, 38*, 32-44. doi:10.1016/j.indmarman.2007.11.003

Walker, O. C., Churchill, G. A., & Ford, N. M. (1979). Where do we go from here?: Selected conceptual and empirical issues concerning the motivation and performance of the industrial salesforce.

Wang, G., & Miao, C. F. (2015). Effects of sales force market orientation on creativity, innovation implementation, and sales performance. *Journal of Business Research, 68*, 2374-2382.

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.

Winterton, J., Delamare-Le Deist, F., & Stringfellow, E. (2006). *Typology of knowledge, skills and competences: clarification of the concept and prototype*: Office for Official Publications of the European Communities Luxembourg.

Yang, B., Kim, Y., & McFarland, R. G. (2011). Individual Differences and Sales Performance: A Distal-Proximal Mediation Model of Self-Efficacy, Conscientiousness, and Extraversion. *Journal of Personal Selling & Sales Management, 31*, 371-382.

Yilmaz, C. (2002). Salesperson performance and job attitudes revisited: An extended model and effects of potential moderators. *European Journal of Marketing, 36*, 1389-1414.

Zablah, A. R., Franke, G. R., Brown, T. J., & Bartholomew, D. E. (2012). How and when does customer orientation influence frontline employee job outcomes? A meta-analytic evaluation. *Journal of Marketing, 76*(3), 21-40.

Zallocco, R., Pullins, E. B., & Mallin, M. L. (2009). A re-examination of B2B sales performance. *Journal of Business & Industrial Marketing, 24*, 598-610. doi:10.1108/08858620910999466

Chapter 3: The Role of Lead Management Systems in Inside Sales Performance

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The role of lead management systems in inside sales performance

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Article Abstract: 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.

Keywords: Inside Sales, Lead Management System, PLS-SEM, Sales Performance.

Note: This Chapter is an Author accepted manuscript submitted to the journal referred to above.

3.1.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, Marshall, & Park 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, Benyoucef, & Andreev 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 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.

3.2. 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 & 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, Jones, Rapp, & Mathieu, 2008; Hunter & Perreault Jr., 2007; 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).

3.2.1. Conceptual Model

The conceptual model (Figure 3.1) 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).

Figure 3.1 appears here

Mediating Variables-to-Sales Performance

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 et al., (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

Hypothesis 1: *Call quantity positively affects sales performance*

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 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

Hypothesis 2: *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

Hypothesis *3: Call quantity positively affects lead follow-up intensity.*

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; Roman & 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 et al., (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:

Hypothesis 4: *Adaptive selling behavior positively affects sales performance*

Selling Skills: Salespeople require certain basic skills for performing the necessary tasks for the sales job (Singh & Venugopal, 2015). Rentz et al. (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.

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 (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 (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

Hypothesis 5: *A salesperson's technical skills positively affect sales performance*

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 et al. (2009b) suggested a positive effect of salesmanship skills on sales performance. Accordingly, we posit that

Hypothesis 6: *A salesperson's salesmanship skills positively affect sales performance*

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

Hypothesis 7: *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

Hypothesis 8: *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

Hypothesis 9: *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 (Gary K 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

Hypothesis 10: *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 be important for organizational CRM endeavours (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

Hypothesis 11: *The use of LMSs increases salespeople's salesmanship skills.*

3.3. 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 3.1). The feedback from experts confirms the reliability and consistency of our measurement items.

Table 3.1 appears here

3.3.1. 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.

3.3.2. 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.

3.4.Results

Table 3.2 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.

Table 3.2 appears here

3.4.1. 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 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). Figure 3.2 shows the results of our structural and measurement models' evaluation of the general model.

Figure 3.2 appears here

3.4.2. 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)*.

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, Ringle, & Sarstedt, 2015; Henseler et al., 2009). 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.

Internal Consistency Reliability: We used Cronbach's alpha (CA) and Composite reliability (CR) to test for internal consistency reliability. Table 3.3 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).

Table 3.3 appears here

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 Figure 3.2 and Table 3.3).

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 3.3).

Discriminant Validity: We assess the reflective constructs for discriminant validity using the Fornell-Larker criterion, cross loadings and the Heterotrait-monotrait (HTMT) ratio. Table 3.4 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.

Table 3.4 appears here

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).

Table 3.5 appears here

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 3.5 illustrates that all HTMT correlations between two constructs are less than 0.782. Additionally, a bootstrapping procedure reaffirms that true correlations between two constructs are less than 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 3.4 and 3.5 as well as Appendix A show the distinctiveness of constructs in our path model.

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).

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., 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.

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 3.6).

Subsequently, we obtained Variance Inflation Factor (VIF) scores to assess multicollinearity. The VIF scores range from 1.004 to 1.077 (see Table 3.6). 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.

Table 3.6 appears here

3.4.3. 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).

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 explain 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.

Significance of Path Coefficients: We ran bootstrapping with 5,000 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). Figure 3.3 and Table 3.7 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.

Table 3.7 appears here

Mediator Analysis: We also assessed the significance of mediator constructs in the model. Table 3.7 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 3.8 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.

Table 3.8 appears here

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 3.9 shows that adaptive selling has a 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.

Table 3.9 appears here

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 3.10 confirms that all endogenous constructs in our path model have predictive relevance as the Q^2 values are all above zero.

Table 3.10 appears here

3.4.4. 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 & 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 3.7), as well as the coefficient determination of endogenous constructs. Figure 3.3 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.

Figure 3.3 appears here

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.

3.5. 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.

3.5.1. 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 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.

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.

3.5.2. 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.

3.5.3. 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 modelling 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).

3.6. 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

Table 3.1: 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 Jr *et al.*, 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)
	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 Jr., 1982; Rentz, Shepherd, Tashchian, Dabholkar, & Ladd, 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, Hughes, & Schillewaert, 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 3.2: 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%**			

Table 3.3: Internal Consistency Reliability, Indicator Reliability and Convergent Validity 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 3.4: 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

Table 3.5: 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 3.6: 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	0.198	0.886	0.376	1.077
	LFU3: Speed	0.911	0.114	**7.989**	0.000	1.077

Table 3.7: 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 = n

Table 3.8: 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	0.005ns	-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

Table 3.9: Effect Size (F2) 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 3.10: 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

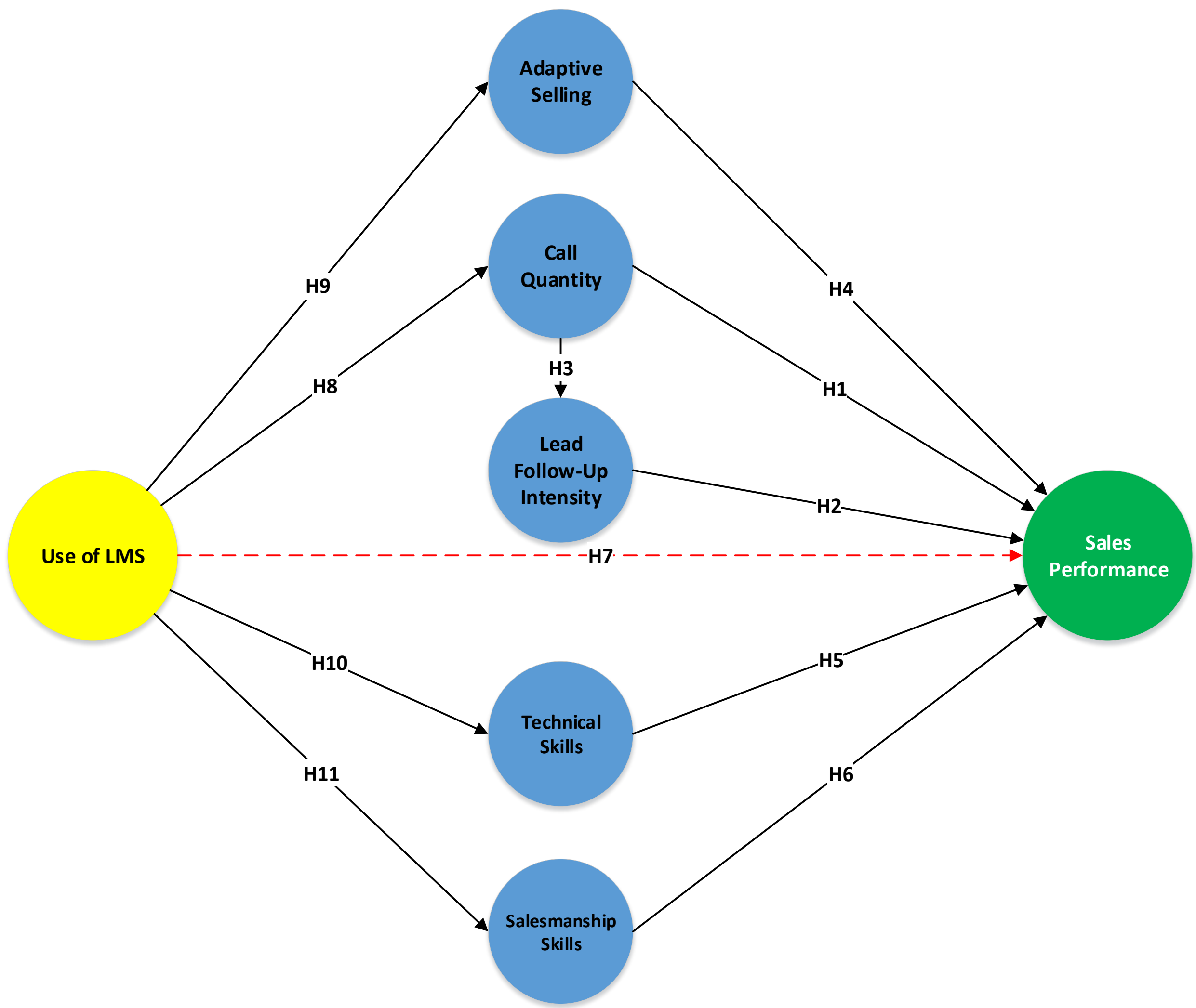


Figure 3.1: Conceptual Model

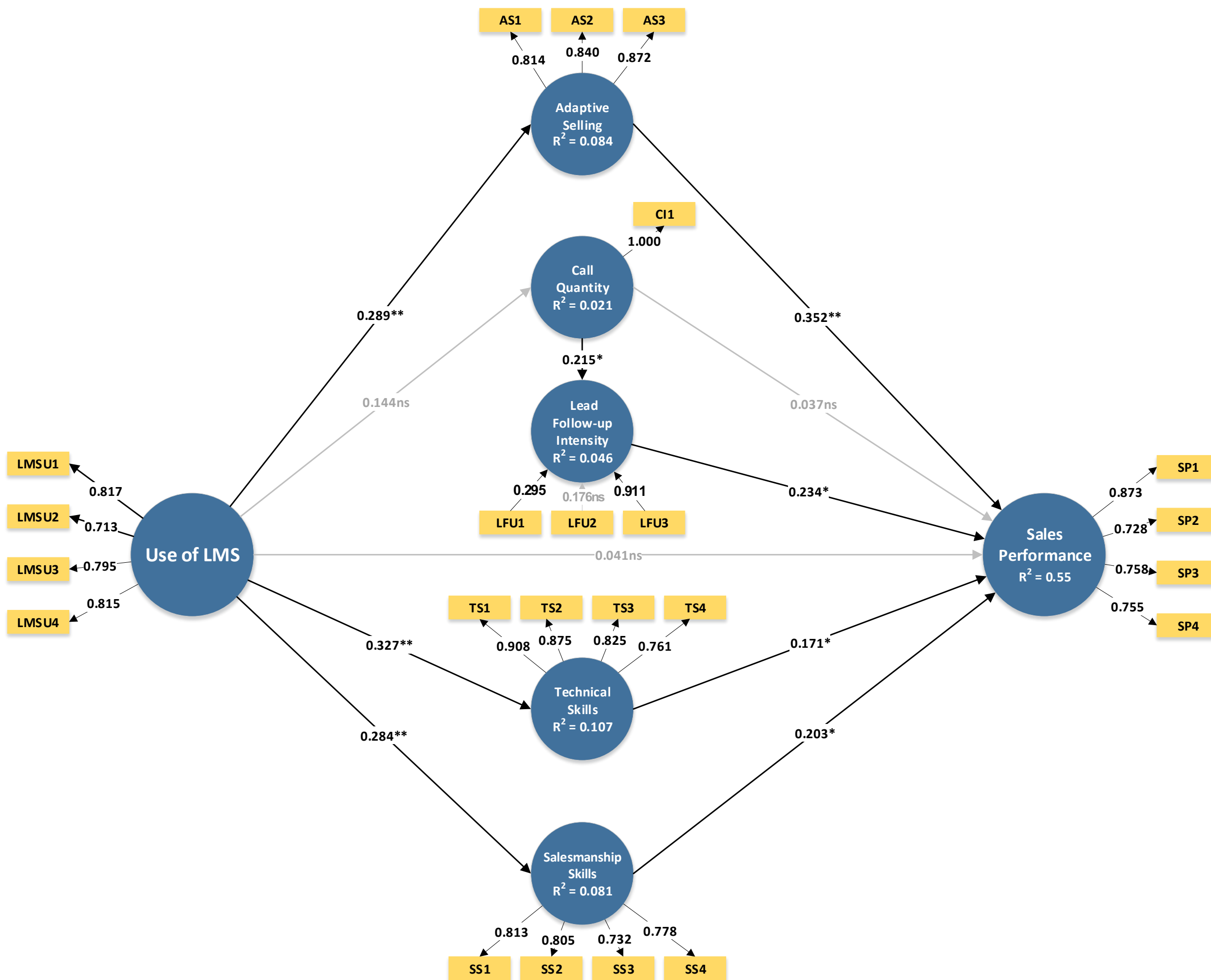


Figure 3.2: Evaluation of Measurement and Structural Models of General Model

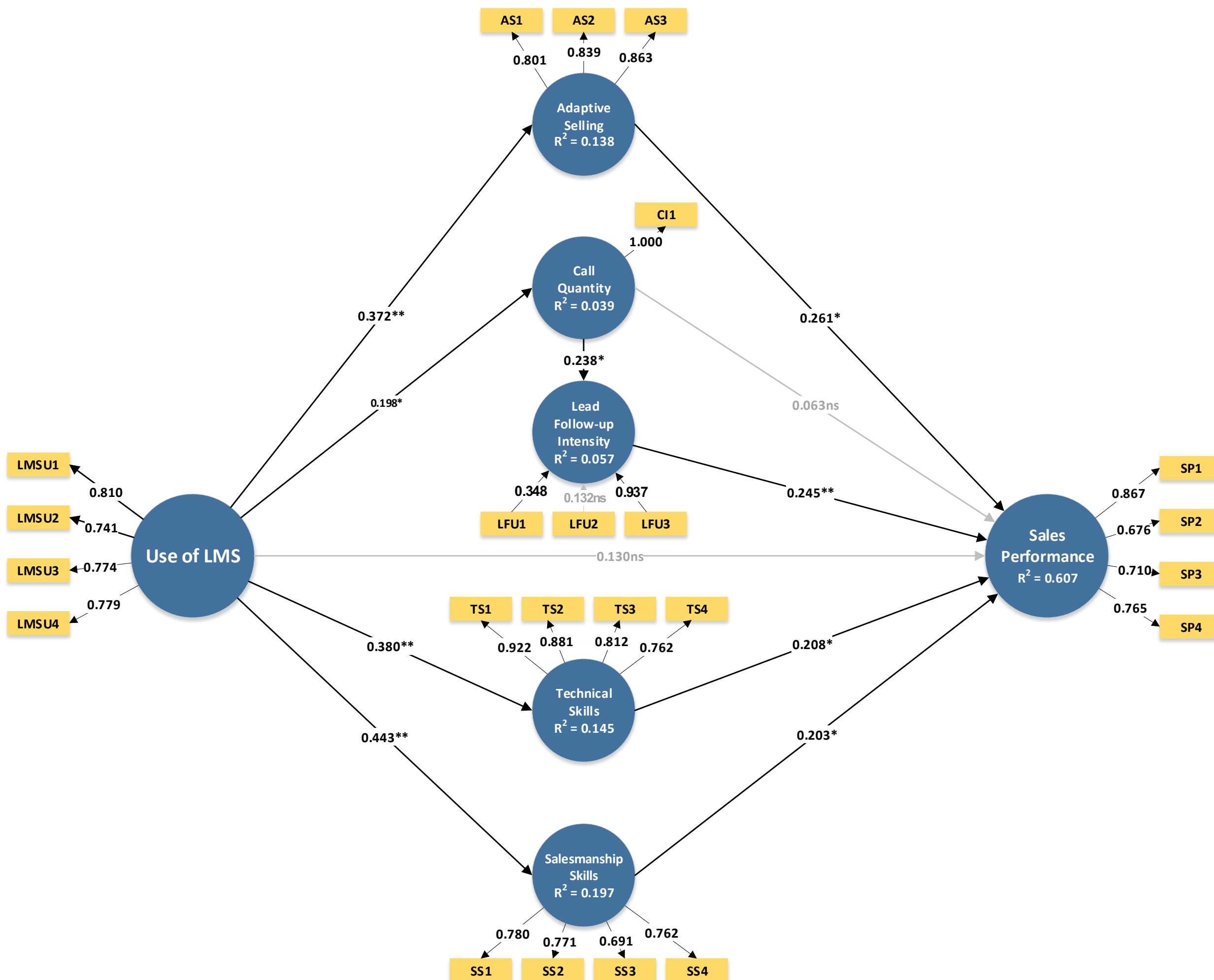


Figure 3.3: Evaluation of Measurement and Structural Models of Queue-Based Model

APPENDIX A:

Table 3.11: 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., 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*. Nova Southeastern University, Ann Arbor. 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*, 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.

Bohanec, M., Borštnar, M. K., & Robnik-Šikonja, M. (2017). Explaining machine learning models in sales predictions. *Expert Systems with Applications, 71*, 416-428.

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 http://dx.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. Second edition. *Hillsdale, NJ*, *20*, 26.

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. (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*, *43*(4), 693–702.

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 Jr, R. A. (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 Jr., D. W., 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 Jr, J. F., 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.

Haliva, F. (2015). 7 Must-Track KPIs for Inside Sales Success. Retrieved June 3, 2017, from http://blog.kryonsystems.com/pss/7-must-track-kpis-for-inside-sales-success

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. In *New challenges to international marketing* (pp. 277–319). Emerald Group Publishing Limited.

Honeycutt Jr., E. D. (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 Jr., W. D. (2007). Making sales technology effective. *Journal of Marketing*, *71*(1), 16–34.

Hunter, G. K., & Perreault Jr, W. D. (2006). Sales Technology Orientation, Information Effectiveness, and Sales Performance. *Journal of Personal Selling & Sales Management*, *26*(2), 95–113.

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 Jr, D. J., & 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.

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.

Roman, 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., & Venugopal, P. (2015). The impact of salesperson customer orientation on sales performance via mediating mechanism. *Journal of Business & Industrial Marketing*, *30*(5), 594–607.

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.

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.

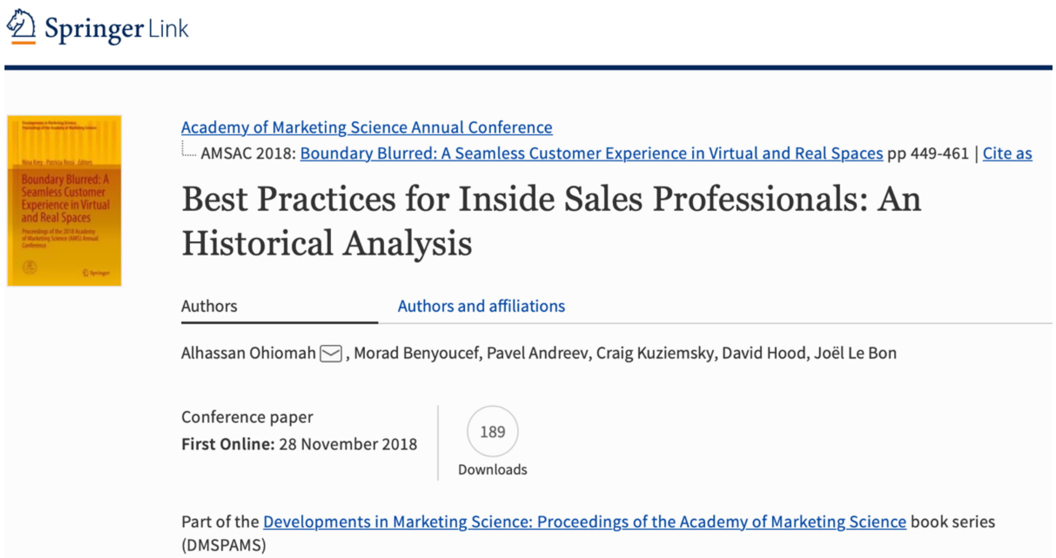
Weitz, B. A., Sujan, H., & Sujan, M. (1986). Knowledge, motivation, and adaptive behavior: A framework for improving selling effectiveness. *The Journal of Marketing*, 50(4), 174–191.

Wold, H. (1985). Partial least squares. *Encyclopedia of Statistical Sciences*.

Yan, J., Gong, M., Sun, C., Huang, J., & Chu, S. M. (2015). Sales pipeline win propensity prediction: a regression approach. Paper presented at the Integrated Network Management (IM), 2015 IFIP/IEEE International Symposium on.

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.

Chapter 4: Best Practices for Inside Sales Professionals: An Historical Analysis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Article Abstract: Big data analytics is an emerging topic that has the potential to significantly improve customer acquisition for inside salespeople, the fastest growing role in the sales industry. However, there has been limited application of Big data analytics in inside sales, especially in regard to the best strategies to engage customers through sales lead optimization. This paper intends to close this gap by providing a comprehensive and longitudinal study of the value of Big data analytics for both B2B and B2C inside sales. Data collected from 43 companies representing several industries through a leading provider of sales by phone software and containing about 47 million call history logs made to over 13 million leads from 2005 to 2016 reveal the best time and best way to optimize lead management practices. Theoretical and managerial contributions are highlighted.

Keywords: Inside Sales, Lead Management, Lead Conversion, Big Data Analytics

Note: This Chapter is an Author accepted manuscript submitted to the Conference referred to above.

4.1.Introduction

Customer acquisition is a fundamental and integral part of any sales organizations' CRM strategy (Ang and Buttle 2006). However, customer acquisition is complex and often based on gut feelings rather than empirical findings (D'Haen et al. 2016). Much of the empirical studies has been directed towards other CRM aspects such as customer retention and development (D'Haen, Van den Poel, and Thorleuchter 2013; Hillebrand, Nijholt, and Nijssen 2011; Tanner et al. 2005). Customer acquisition is important for start-ups and companies looking to acquire new customers and enter new markets (Ang and Buttle 2006; Buttle 2009; Kamakura et al. 2005). The question of customer acquisition is critical within inside sales contexts—sales that are performed remotely using information and communication technology (ICT)—where specific sales' roles are dedicated to lead generation and qualification (Zoltners, Sinha, and Lorimer 2013). Also, existing companies loose on average 10% of customers annually (Coe 2004); hence, they never abandon their quest for new customers to substitute those lost (D'Haen et al. 2016). Moreover, companies need to put their existing customers back into their acquisition process in order to offer them complementary or supplementary products.

Companies invest in marketing, through advertising, web campaigns and trade shows to generate leads (i.e., potential customers) for sales people to follow-up on and convert into appointments and/or purchases (Sabnis et al. 2013; Smith, Gopalakrishna, and Chatterjee 2006). However, how to make successful lead follow-up represents a key challenge for industry practitioners (Ohiomah, Benyoucef, and Andreev 2016; Sabnis et al. 2013; Smith, Gopalakrishna, and Chatterjee 2006). Within an inside sales context, there are several dynamics in play when salespeople make decisions on which sales leads to pursue (D'Haen et al. 2016; D'Haen, Van den Poel, and Thorleuchter 2013; Monat 2011). Salespeople rely on subjective intuition, scholarly suggestions, and gut feeling to make such decisions. This approach is not effective and can redirect company resources to the wrong leads (D'Haen, Van den Poel, and Thorleuchter 2013). Reports indicate that approximately 20% of salespeople's time is spent on selecting prospects to contact (D'Haen, Van den Poel, and Thorleuchter 2013). Moreover, delays in lead follow-up and directing resources to the wrong leads reduce the likelihood of converting leads to sales and eventually hurt the company at the downstream (Smith, Gopalakrishna, and Chatterjee 2006).

Existing lead conversion studies have suggested models that could help improve lead qualification (i.e., converting prospects into leads (D'Haen, Van den Poel, and Thorleuchter 2013) with an explicit assumption that lead qualification will ultimately improve conversion of leads into sales. Yet, studies indicate that on average, only 10% of prospects are qualified as leads and only 1-5% of leads will eventually convert to sales and become customers (Coe 2004). Lower conversion rates of leads increase the cost of customer acquisition for companies. Although some studies focus on conversion of leads to sales and customers (e.g., Monat 2011) they do not usually rely on gathering and implementing data-driven insights.

Big data analytics—the use of innovative methods and tools to discover insights, trends, and relationships existing within high volume, variety and velocity data, predict future trends and outcomes, and suggest alternative options to help decision makers optimize their business processes and performance based on their data, business objectives, requirements, and constraints (Delen and Demirkan 2013; Krumeich, Loos, and Werth 2015; Shim et al. 2015; Sun, Zou, and Strang 2015; Watson 2014)—can automate decision making and reduce the use of human intuition (Bohanec, Borštnar, and Robnik-Šikonja 2017; Yan, Zhang, et al. 2015). Advances in Big data analytics technology could support customer acquisition for inside sales (Atkins et al. 2016; Rygielski, Wang, and Yen 2002). Practitioners can use sources of historical data about leads, customers, and markets to identify valuable sales opportunities and customers, better strategize cross-selling and up-selling efforts, predict sale likelihood and future behaviour and make proactive data-driven decisions (Rygielski, Wang, and Yen 2002).

While Big data analytics can provide insight on inside sales and lead conversion activities, to date, data driven approaches to inside sales is understudied. To the best of our knowledge, there is no academic research that has investigated lead conversion by looking at key variables of the calling task itself. Although factors such as time of call and call attempts to lead are consistent and applicable to the majority and probably all inside sales businesses, there is a dearth of data driven research offering insights on the factors that may help improve lead conversion ratios. This research aims to address that shortcoming by investigating how Big data analytics can be used to discover insights about the inside sales lead management process using call history logs collected from different companies over a long time period. More precisely, the current work is aimed at discovering insights that can help understand and optimize the lead management process.

Particularly, we seek to answer the following key questions, "*When is the best time to contact a lead?*" and *"What is the best way to engage with a lead?"*

This research makes several contributions to the literature. From a theoretical perspective, the findings provide a better understanding of the best timeframes, number of calls, and best odds for first contact, along with more accurate insights on the number of contact attempts needed to engage customers' interest. From a methodological and sampling standpoint, this research also contributes to the literature through a comprehensive data collection process and Big data analytics involving 43 companies of several industries and containing about 47 million call history logs made to over 13 million leads for 11 years. From a managerial standpoint, the findings help discriminate between the effectiveness of web leads and non-web leads in B2C and B2B settings. Results also help appraise the importance of inside salespeople's persistency, consistency, and speed of calls, and thus provide valuable insights on effective time management strategies to support lead conversion activities.

4.2.Literature Review

The growth and survival of most companies is highly dependent on the success of their sales objectives (Delgado-Gómez et al. 2011), particularly, the acquisition of new customers (Coe 2004). Leads are an important component of every business organization that sells products or services (Monat 2011; Ohiomah, Benyoucef, and Andreev 2016; Yan, Gong, et al. 2015), irrespective of whether the leads come from a new prospect or an existing customer of the organization (Monat 2011). Although the goal is to convert every lead into sales and ultimately customers, the reality is that some leads are always better than others and have better chances of converting to an appointment and/or purchase (Monat 2011), hence, salespeople usually contact those they presume have a high likelihood of sales. Currently, prioritization of contacts is mostly based on subjective intuition of salespeople, scholarly suggestions, and self-competence and experience (D'Haen et al. 2016; D'Haen, Van den Poel, and Thorleuchter 2013; Monat 2011). Some advanced organizations implement effective, efficient, and reliable lead management guidelines based on their business heuristics rules, which differ from organization to organization. Hence there is no consensus across the inside sales industry with regards to lead prioritization. Wrong prioritization strategies leads to opportunity loss, inaccurate sales forecast, resource allocation on the wrong leads and redirection of marketing campaign efforts (Järvinen and

Taiminen 2016; Monat 2011; Sabnis et al. 2013). Estimating the likelihood of converting a lead is fundamental for sales practitioners in order to replace subjective or ad-hoc human ranking practices of sales leads (Yan, Zhang, et al. 2015). Yet, there is limited literature that provides insights into lead conversion (Monat 2011; Yan, Gong, et al. 2015). In the next section we review literature on sales lead conversion.

The literature on sales lead conversion can be categorized into two groups. One is related to the performance, skills, and behavior of a salesperson during sales interaction, and another one on the characteristics of prospects or leads. Several studies examined aspects of a salesperson performance, skillset and what behavioral features portrayed during sales interactions can be used to determine and improve lead conversion and ultimately sales outcomes (e.g., Sabnis et al. 2013; Smith, Gopalakrishna, and Chatterjee 2006). Even though the former is a crucial aspect of sales lead conversion, it will not be a focus of the current work because of the difficulty to access appropriate data within this research context. Thus, our research focus is on the latter.

The characteristics of prospects or leads play a significant role in determining sales lead conversion. The literature suggests two main strategies for that. First, profiling prospects based on predefined features (e.g., Monat 2011), and second, using historical data about existing customers to classify prospects (e.g., D’Haen, Van den Poel, and Thorleuchter 2013). Using the profiling approach, Monat (2011) adapted factors that determine customer purchase decisions to develop a model to predict the likelihood of converting a lead into an appointment or purchase. The model relies on lead characteristics such as source, timeframe, decision authority, and whether the customer is a current or past customer. Most models developed with this approach are conceptual and not empirically validated (e.g., Monat 2011). In addition, not all lead characteristics proposed in (Monat 2011) and other studies are applicable and/or readily available to every salesperson before sales interactions (Järvinen and Taiminen 2016). Thus, the significance and availability of the proposed set of lead characteristics varies from organization to organization (Monat 2011). Most organizations rely on publicly available information for their understanding of leads’ purchase interest (Järvinen and Taiminen 2016; Long, Tellefsen, and Lichtenthal 2007).

Following the second approach of profiling based on existing customers, D’Haen & Van den Poel (2013) introduced a model to guide salespeople in selecting the right prospects that could be converted to leads. The study was the first of its kind to respond to Monat's (2011) call for sales lead conversion models. Later, Yan and colleagues 2015 proposed a model that estimates the win-propensity of sales leads overtime. The model captures and estimates the impact of attributes of individual salesperson activities as well as personalized lead profile on the win outcome. The study was applied in a field-selling context. Furthermore, Bohanec et al., (2016) introduced a B2B sales classification-forecasting model using insights from B2B salespeople. These insights were denoted as historical sales data labeled with attributes of the sales process. D'Haen et al., (2016) proposed a Decision Support System (DSS) for lead qualification from a list of prospects that are most likely to convert into sales and ultimately into customers. They used information (e.g., industry and company size) located on the websites of prospects (only companies with websites), and accordingly, employed text mining to qualify prospects as leads who are ready for contact.

In summary, first, the majority of the above literature have focused on lead qualification (i.e., converting prospects to leads) and not on conversion of leads to first time or reoccurring purchases (i.e., customers). Second, the amount of data used for investigations by these studies is considered small, and limited to a single source (e.g., a company) thus their findings and models may lack external validity and applicability. Also, these studies do not provide enough data-driven insights into practices that can improve lead conversion outcomes. Factors of the selling task (e.g., time of call, call attempts to lead) are crucial in estimating the probability that a sales lead could convert to an appointment and/or sale. However, to the best of our knowledge, there is no academic literature (only industry white papers) that has investigated lead conversion by looking at key variables of the calling task itself. Factors such as time of call and call attempts to lead are consistent and applicable to the majority and probably all inside sales businesses. Yet there is a dearth of data driven studies offering insights on the factors that may help improve lead conversion ratios. This paper aims to address that shortcoming by demonstrating how Big data analytics can be used to discover insights about the inside sales lead management process using call history logs collected from different companies.

4.3.Research Method

The design of this study adapts the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework Chapman et al., (2000). We collected data on 43 companies representing several industries through a leading provider of sales by phone software. This data contains about 47 million call history logs made to over 13 million leads from 2005 to 2016. The types of sales calls performed by inside salespeople within this data include: calling to qualify leads, calling to develop and manage leads (i.e., nurturing leads), calling for proposal or sales closing, calling to up-sell or cross-sell to existing customers, calling to build strong relationships with key customers, and calling for service and support. The data collected includes 58 variables that were mostly generated automatically by the CRM lead management system during lead calling activity (i.e., time of call, State of lead). This kind of data can help to understand the best time to call leads, best response time to lead, and best lead call practices such as call attempts needed to connect with a lead. The 43 companies operate in 7 countries representing 4 continents, with the majority of the call history originating from the United States.

As mentioned above, the data was generated automatically by the CRM management system during lead calling activity and thus, most of the data was standardized. Nevertheless, the data still needed to be cleaned because of the presence of irrelevant variables and a high number of classes in some categorical variables. In cleaning the data, observations were completely standardized, additional variables were created from existing data fields to be useful for analysis, and irrelevant variables were removed. The result code (i.e., outcome variable) was recoded into 3 classes from 13,936 unique result codes. We deleted variables that generated a large amount (over 50%) of missing values (e.g., Call back Time, Retry Time and Date). Additionally, we created a day (Monday to Sunday), time (24hr) month (January to December) and year variables from the call date and time variable. We also created variables that calculate the number of days and time from when a lead was added to when it was called. Ultimately, we retained 5 numeric and 12 categorical variables. We used R Studio (version 3.3.2) to clean, prepare, analyze and visualize the dataset.

We start our analysis by computing the distribution of call outcomes across both business models (B2B and B2C) to establish a baseline using both first and all call contact attempts. Then we analyze the distribution of call outcomes across a 10-hour timeframe (8am to 6pm), weekday (Monday to Sunday) and 10//7 periods on both business models to see how they diverge from the established baseline using both approaches.

We analyzed response time to leads and call attempts to lead. These measures are consistent with key industry performance indicators (KPIs) with regards to lead management (Elkington and Oldroyd 2016; Haliva 2015; VanillaSoft 2014).

- **Response Time to Lead:** Here, we only used “web leads” to compute time to lead because data about such leads was generated by the system as soon as a query was made. As for non-web leads, it is uncertain when they were actually generated. We only know when they were imported into the lead management system. Hence, response time to lead analysis of non-web leads would provide misleading results. Additionally, we removed web leads that were generated between 7pm and 7am and those generated over the weekend because it is assumed that most salespeople do not work within these timeframes. We used cross-tabulation and frequency distribution plots of call results overtime of web leads.
- **Call Attempts to Lead:** We computed the average and median amount of call attempts needed to connect with a lead on various call results using both business models and across all industries.
- **Response Time and Call Attempts to Lead**: Finally, we explored the impact of response time to lead and call attempts on lead outcomes. We only consider leads for which outcome was positive. The goal was to see how these factors together affect the outcome of the call. We limited the display of results to leads contacted within the first 20 days for better visualization.

4.4.Findings

For first call attempt, our baseline shows that only that 25.5% (Negative 14.2%, Positive1 1.3%) resulted in a live contact with a lead for B2B companies, while 22.7% (Negative 13.2%, Positive 9.5%) resulted in a live contact with a lead for B2C companies. The no-contact ratio for first contact attempt was 74.5% and 77.3%for B2B and B2C companies respectively. For all call attempts, our baseline shows that only 21% (Negative 10%, Positive 11%) of all call attempts resulted in a live contact with a lead for B2B companies, while 13% (Negative 8%, Positive 5%) resulted in a live contact with a lead for B2C companies. The no-contact ratio was 79% and 87% for B2B and B2C companies respectively. This ratio is consistent with industry standards (Tousley 2015).

Our analysis of the best time to call for B2B companies shows that the contact ratio increases to 33% at 6pm (first contact attempt), and to 22% between 9am and 11 am (all contact attempts). For the best time to call to get a positive response, we found that 8am (both first and all call attempts) and 5pm (all call attempts) have the highest ratio (average of 61% within the contact group). For the best days to call, we found no significant increase or decrease from the baseline for first contact attempt. Moreover, contact ratio increases to 22% on Tuesdays and Wednesdays, and goes down to 19% on Fridays (all contact attempts). The analysis of both time and day shows the highest contact ratio (all contact attempts) over all to be on Tuesday from 9am to 10am.

For B2C companies, the times of day with the highest contact ratio are 4pm (26%), 5pm (33%) and 6pm (32%) for first call attempts, and 5pm (18%) and 6pm (17%) for all call attempts. Significantly, 8am (9%) to 9am (10%) have the lowest contact ratio, yet, 8am to 9am and 4pm are the best times to call for a positive result for all call attempts. Contact ratio is up to 24% and 14% on Mondays and Tuesdays for first and all call attempts respectively. The analysis of time and day shows that Monday and Tuesday 5pm to 6pm and Sunday at 9am have the best successful contact ratio all contact attempts overall. Also, Sunday 8am has the highest positive result, however, that timeslot only represents a small ratio of calls made by salespeople.

Figure 4.1appears here

To instigate response time to web leads and its relative impact, we ended up with 15 million call history logs of over 2 million web leads. As illustrated in Figure 4.1, our analysis indicates that contacting a lead within the first hour is important for making live contact with a lead on the first attempt and for improved positive outcome with those leads in the long run. The best window starts after 10 minutes of a query and goes down rapidly after the first hour.

Table 4.1 appears here

The analysis shows that the average number of call attempts necessary for a positive outcome with a lead is 5 for B2B companies and 5.6 for B2C companies (see Table 4.1). The findings also shows that companies involved in B2C appointment setting services and financial consulting need an average of at least 20 contact attempts for a positive outcome with a lead. Whereas companies involved in B2C third party marketing, janitorial, or B2B insurance services only need as low as 3 contact attempts for a positive outcome with a lead. This suggests that contact attempt influence on lead outcome varies from industry to industry.

Figure 4.2 appears here

Furthermore, we estimate the association between how long a lead has been in the sales cycle with how effective contact attempts to lead affect various outcomes (see Figure 4.2). Here, we found a trend in strategically spacing contact attempts to leads. The majority of leads positive outcomes have an average of 3 to 4 contact attempts made within the first 4 to 5 days of a lead being in the sales cycle (see Figure 4.2). Subsequent contact attempts are spaced for another 5 days.

4.5.Discussion and Implications

Inside salespeople regularly receive large volumes of leads from the marketing department. However, there is little work that has looked at how to support lead conversion. This paper uses Big data analytics to provide insights about lead conversion in inside sales. Our findings make several contributions to theory and practice. To the best of our knowledge, this is the first Big data-oriented study to investigate lead management calling practices in order to provide insights into factors that can help improve contact ratio and lead conversion outcomes. Prior studies on this topic have been limited by data size and diversity (e.g., Elkington and Oldroyd 2016), possibly limiting their generalizability.

Elkington & Oldroyd's (2016) lead response management study indicates that Wednesdays and Thursdays are the best days to make contact with a lead or a qualified lead, while 8am and 4pm to 5pm are the best times to call to qualify a lead. Slightly in line with the findings of Elkington & Oldroyd (2016), we found 8am and 5pm for B2B, and 8am to 9am for B2C to be the best times to call for a positive outcome, which may include lead qualification. It should be noted that Elkington & Oldroyd (2016) only used the first contact attempts of about 10,000 leads to investigate the best time and day to contact to qualify a lead. In contrast, we used both first and all contact attempts (about 47 million) of over 13 million unique leads. The size and diversity of our dataset makes our findings more significant. Additionally, we found that 9am to 11 am for B2B and 5pm to 6pm for B2C are the best times to call to make live contact with a lead. Also, 6pm for B2B and 5pm to 6pm for B2C are the best times to make first call attempt for live contact with a lead.

Meanwhile, Tuesdays and Wednesdays for B2B, Mondays and Tuesdays for B2C are somewhat the best days to call to make live contact with a lead. Particularly, we found that Tuesday 9am to 10am (B2B), as well as Monday and Tuesday 5pm to 6pm and Sunday 9am (B2C) to have the most successful contact ratio. Even though we found these timeframes to be optimal for a better contact connect ratio, we do not suggest that salespeople only make calls at these times. Rather, we suggest that more resources should be used to improve the number of calls being made at these timeframes. This is because we found that times with the highest ratio of contact as well as positive result ratio have a low proportion of total calls made. This means, there are less calls (low coverage) being made by salespeople at times with the best call contact and positive result ratios. An alternative explanation we found within the data is that less calls are being made at these timeslots because salespeople are already spending time on calls (i.e., call duration) with leads they have already made live contact with. Therefore, although there is lower call coverage there is higher call duration and higher call quality.

Industry studies show that the odds of qualifying a recently generated lead decrease over a factor of 10 in the first hour, and the best odds are if the contact occurs within the first five minutes based on first contact attempts (Elkington and Oldroyd 2016). We conducted our analysis using both first contact attempt and all other contact attempts after web leads enter the system. Our findings differ from other studies (Elkington and Oldroyd 2016). Figure 4.1 illustrates that the best odds for first contact are between 10 - 60 minutes for query, and not within the first 5 minutes. It is uncertain why contact momentum only picks up after the first 10 minutes. A possible explanation could be that salespeople might be responding too quickly, which may overwhelm leads who are not yet ready to make a decision. Regardless, quick response to a lead increases lead qualification and lead conversion to sales. Additionally, we found that leads that start positive from the first attempt eventually lose momentum significantly in the long run. Accordingly, we advise against using only first contact attempts to gauge the impact of response time to web leads outcome.

Furthermore, industry studies indicate that 10% of sales are closed after 4 follow-up contacts and 80% of sales are closed between 5 and 12 follow-up contacts (Elkington and Oldroyd 2016; Haliva 2015). Our findings were consistent with the suggested industry average of follow-up attempts needed for a positive outcome with a lead. However, we identified that the number of contact attempts needed is growing and the maximum contact attempts are no longer in the tens but rather in the hundreds. We also identified that call attempts required for a positive outcome vary from industry to industry. For instance, the call attempts required for service oriented industries (e.g., appointment services, financial services) is more than the call attempts required for selling in other industries like communications. The same can be said of lead types and the type of product or services being sold. The call attempts required to sell to a qualified lead is lesser than the call attempts required to sell to an unqualified lead. Finally, we encourage practitioners to put more effort towards responding faster to all leads with a more persistent follow-up at the start of the lead sales cycle.

4.6.Limitations And Futher Research

This study has some limitations that provide opportunities for further research. First, data from one industry (Education recruiting service) represents over one third of the data we used. The majority (75%) of leads are from the United States. This may have an impact on the general validity of our findings. Also, we did not explore individual lead characteristics (e.g., location of lead, revenue, etc.) on the best time to call and how best to engage with a lead. This offers a unique opportunity to add to prior literature on lead profiling. We believe that prioritizing which lead to pursue, and how or when to engage with this lead are two sides of a coin. For instance, a lead may be the best lead to chase next based on profile similarity of existing customers, however, the time and medium used to contact the lead might reduce the chances of conversion of that lead. Accordingly, that opportunity might be lost. There is little to no trade-off between both sides. This represents a gap yet to be filled in the literature. The next phase of this ongoing study is to fill this gap.

Table 4.1: Call attempts central tendency distribution

B2B			
Call Result	**Mean**	**Median**	**Max**
Negative	2.94	1.00	219
Positive	4.97	2.00	230
No Contact	4.47	2.00	159
B2C			
Negative	4.64	1.00	450
Positive	5.63	2.00	454
No Contact	13.67	4.00	457

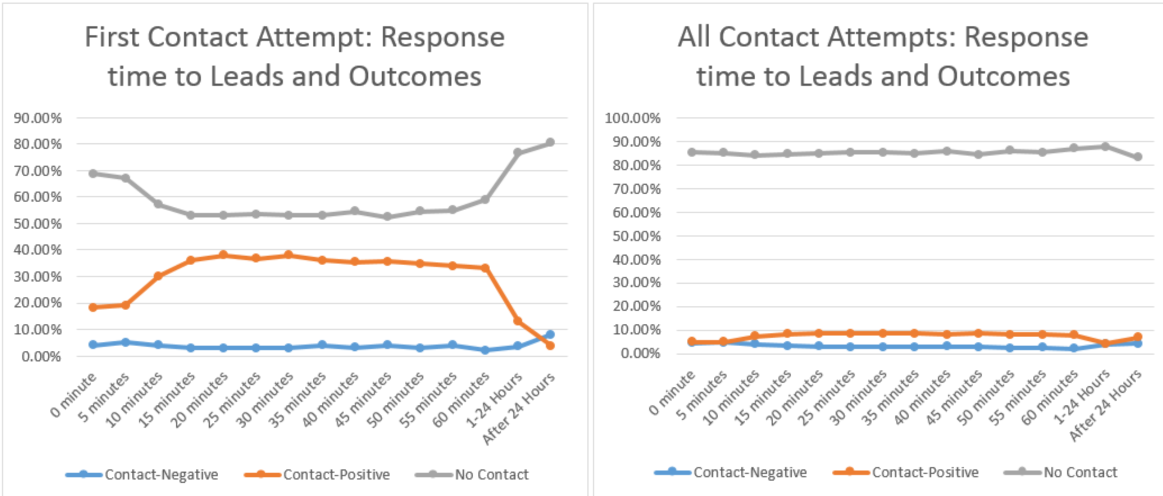

Figure 4.1: Response time to lead and outcomes (first & all Contact Attempts)

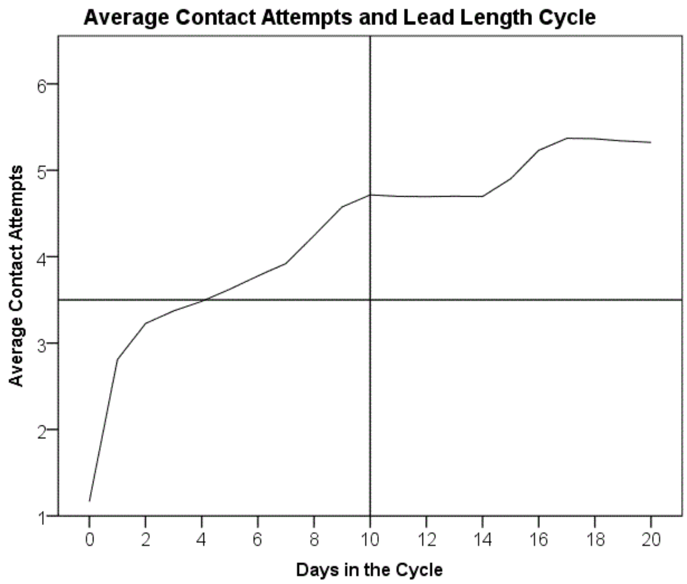

Figure 4.2: Call Attempts and Sales Cycle Length

References

Ang, Lawrence and Francis Buttle (2006), “Managing for successful customer acquisition: An exploration,” *Journal of Marketing Management*, 22 (3–4), 295–317.

Atkins, Charles;, Maria; Valdivieso de Uster, Mitra; Mahdavian, and Lareina Yee (2016), “Unlocking the power of data in sales,” *Mckinsey*, (accessed July 20, 2001), [available at http://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/unlocking-the-power-of-data-in-sales?cid=analytics-alt-mip-mck-oth-1612].

Bohanec, Marko, Mirjana Kljajić Borštnar, and Marko Robnik-Šikonja (2016), “Integration of machine learning insights into organizational learning: A case of B2B sales forecasting,” in *Blurring the Boundaries Through Digital Innovation*, Springer, 71–85.

———, ———, and ——— (2017), “Explaining machine learning models in sales predictions,” *Expert Systems with Applications*, 71, 416–28.

Buttle, F (2009), “Managing the customer lifecycle: Customer acquisition,” *Customer relationship management: Concepts and technologies*, 225–54.

Chapman, Pete, Julian Clinton, Randy Kerber, Thomas Khabaza, Thomas Reinartz, Colin Shearer, and Rudiger Wirth (2000), “CRISP-DM 1.0 Step-by-step data mining guide.”

Coe, John M (2004), “The integration of direct marketing and field sales to form a new B2B sales coverage model,” *Journal of Interactive Marketing*, 18 (2), 62–74.

D’Haen, Jeroen, Dirk Van den Poel, and Dirk Thorleuchter (2013), “Predicting customer profitability during acquisition: Finding the optimal combination of data source and data mining technique,” *Expert systems with applications*, 40 (6), 2007–12.

———, ———, ———, and Dries F Benoit (2016), “Integrating expert knowledge and multilingual web crawling data in a lead qualification system,” *Decision Support Systems*, 82, 69–78.

Delen, Dursun and Haluk Demirkan (2013), “Data, information and analytics as services,” Elsevier.

Delgado-Gómez, David, David Aguado, Jorge Lopez-Castroman, Carlos Santacruz, and Antonio

Artés-Rodriguez (2011), “Improving sale performance prediction using support vector machines,” *Expert systems with applications*, 38 (5), 5129–32.

Elkington, David and James Oldroyd (2016), “The Best Practices for Lead Response Management,” (accessed June 3, 2017), [available at https://www.insidesales.com/wp-content/uploads/2016/04/LRM-info-graphic-poster-16-5x21-5.pdf?f4bf21&f4bf21].

Haliva, F (2015), “7 Must-Track KPIs for Inside Sales Success.,” (accessed June 3, 2017), [available at http://blog.kryonsystems.com/pss/7-must-track-kpis-for-inside-sales-success].

Hillebrand, Bas, Jurriaan J. Nijholt, and Edwin J. Nijssen (2011), “Exploring CRM effectiveness: An institutional theory perspective,” *Journal of the Academy of Marketing Science*, 39 (4), 592–608.

Järvinen, Joel and Heini Taiminen (2016), “Harnessing marketing automation for B2B content marketing,” *Industrial Marketing Management*, 54, 164–75.

Kamakura, Wagner, Carl F Mela, Asim Ansari, Anand Bodapati, Pete Fader, Raghuram Iyengar, Prasad Naik, Scott Neslin, Baohong Sun, and Peter C Verhoef (2005), “Choice models and customer relationship management,” *Marketing Letters*, 16 (3), 279–91.

Krumeich, Julian, Peter Loos, and Dirk Werth (2015), “Enhancing organizational performance through event-based process predictions.”

Long, Mary M, Thomas Tellefsen, and J David Lichtenthal (2007), “Internet integration into the industrial selling process: A step-by-step approach,” *Industrial Marketing Management*, 36 (5), 676–89.

Monat, Jamie P (2011), “Industrial sales lead conversion modeling,” *Marketing Intelligence & Planning*, 29 (2), 178–94.

Ngai, Eric W T, Li Xiu, and Dorothy C K Chau (2009), “Application of data mining techniques in customer relationship management: A literature review and classification,” *Expert systems with applications*, 36 (2), 2592–2602.

Ohiomah, Alhassan, Morad Benyoucef, and Pavel Andreev (2016), “Driving Inside Sales Performance with Lead Management Systems: A Conceptual Model,” *Journal of Information Systems Applied Research*.

Rygielski, Chris, Jyun-Cheng Wang, and David C Yen (2002), "Data mining techniques for customer relationship management," *Technology in society*, 24 (4), 483–502.

Sabnis, Gaurav, Sharmila C Chatterjee, Rajdeep Grewal, and Gary L Lilien (2013), "The sales lead black hole: On sales reps' follow-up of marketing leads," *Journal of marketing*, 77 (1), 52–67.

Shim, J P, Aaron M French, Chengqi Guo, and Joey Jablonski (2015), "Big data and analytics: Issues, solutions, and ROI," *Communications of the Association for Information Systems*, 37 (1), 797–810.

Smith, Timothy M, Srinath Gopalakrishna, and Rabikar Chatterjee (2006), "A three-stage model of integrated marketing communications at the marketing–sales interface," *Journal of Marketing Research*, 43 (4), 564–79.

Sun, Zhaohao, Huasheng Zou, and Kenneth Strang (2015), "Big data analytics as a service for business intelligence," in *Conference on e-Business, e-Services and e-Society*, Springer, 200–211.

Tanner, John F, Michael Ahearne, Thomas W Leigh, Charlotte H Mason, and William C Moncrief (2005), "CRM in sales-intensive organizations: A review and future directions," *Journal of Personal Selling & Sales Management*, XXV (2), 169–80.

Tousley, Scott (2015), "107 Mind-Blowing Sales Statistics That Will Help You Sell Smarter [SlideShare]," (accessed June 6, 2017), [available at https://blog.hubspot.com/sales/sales-statistics#sm.00008mrcbd20jd44pwl2mvw9d0wbu].

VanillaSoft (2014), "4 Ways Queue-based Lead Management is Shaping the Inside Sales Industry | VanillaSoft," (accessed June 3, 2017), [available at https://www.vanillasoft.com/resources/white-papers/queue-based-lead-management].

Watson, Hugh J (2014), "Tutorial: Big data analytics: Concepts, technologies, and applications," *Communications of the Association for Information Systems*, 34 (1), 1247–68.

Yan, J, M Gong, C Sun, J Huang, and S M Chu (2015), "Sales pipeline win propensity prediction: A regression approach," *Integrated Network Management (IM), 2015 IFIP/IEEE International Symposium on*.

———, C Zhang, H Zha, M Gong, C Sun, J Huang, Stephe Chu, and Xiaokang Yang (2015), “On Machine Learning Towards Predictive Sales Pipeline Analytics,” in *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence*, AAAI’15, AAAI Press, 1945–51.

Zoltners, Andris A, PK Sinha, and Sally E. Lorimer (2013), “The Growing Power of Inside Sales,” *Harvard Business Review*.

Chapter 5: Drivers of Team-based Inside Sales performance in B2B Selling: A Data Driven Study

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Article Abstract: When it comes to B2B Inside Sales, there is a lack of empirical understanding of team-based factors that drive performance, particularly at different stages of the sales pipeline. This paper aims to address such lack of understanding by focusing on predictor variables that are related to team characteristics as well as those related to teams' interactions with Lead Management Systems (LMSs). In this study, we rely on data from the B2B inside sales operations of Insurance and Marketing & Advertising companies. We use Latent Dirichlet Allocation (LDA) and Jenks Break Natural Breaks Optimization to classify the different stages of sales performance and discretize levels of performance at each stage. Subsequently, we use multinomial logistic regression to regress the tiered teams for each performance ratio to our predictor variables. Our results show that the later stages of the sales pipeline rely more on team experience and actions other than calling, such as team goal monitoring and task input. Earlier stages rely more on repetition of tasks. Although team-based sales performance has been measured before, never has it been measured at different stages of the sales pipeline. Hence, our study is a first step towards discovering how to optimize team-based selling within the realm of industrial marketing.

Keywords: Sales Team; Sales Performance; Sales Pipeline; Multinomial Logistic Regression; Text Mining

Note: This Chapter is an exact copy submitted to the journal referred to above.

5.1.Introduction

Team-based business-to-business (B2B) selling is a growing trend, with over 75% of companies using sales teams (Cummings, 2007; Salesforce, 2015). Modern sales have used team selling and group selling interchangeably, however the term "team" better defines the assigned clusters of salespeople as they are bounded by a shared objective. Team-based B2B selling is defined as a sales approach where two or more people with different skills and experience work collaboratively with prospects and leads, being dependent on each other's activities, and sharing a common goal of coordinating resources and managing ongoing sales relationships (Rajagopal & Rajagopal, 2008; Salas et al., 1992). White papers published by consulting and sales practitioners vouched for team-based selling's sustained prominence in organizational design. Deloitte, in their report on Human Capital Trends, found that sales organizations are increasingly employing teams (Deloitte, 2016). Salesforce surveyed over 3100 global sales professionals to find that top performers were almost three times more likely to be engaged in collaborative selling (i.e., team-based selling) compared to underperformers (Salesforce, 2015). One practitioner study analyzed more than 20,000 B2B sales opportunities to conclude that team-based selling can increase the likelihood of closing a deal by about 250% (Gong, 2017). The high adoption of team-based selling was driven by (1) the growing number of stakeholders on the buying organization's side, and (2) the increasing complexity of the selling process (Adamson et al., 2014; Deloitte, 2016; Smith & Barclay, 1993). In the rare instances where the performance of team selling and individual selling has been contrasted, team selling was found to be more efficient (Batt, 1999). Garrett and Gopalakrishna (2017) found that people performed better at team tasks than at individual tasks, which shows the importance of team selling, not just as a practice in of itself, but as the better method of selling. Additionally, team-based factors have a moderating effect on individual performance (Carboni & Ehrlich, 2013). Hence, team selling adds value at both the team level and individual level.

Despite the acknowledgement of the importance of B2B team selling by practitioners, academic research on the subject remains scarce (Moon & Armstrong, 1994; Mullins & Panagopoulos, 2019; Perry et al., 1999). In particular, we witness a lack of research dedicated to the drivers of team-based selling performance. We also witness a need to understand the team-based constructs that would explain the variance of performance in Inside Sales. Inside sales are defined as organized sales that are conducted remotely or virtually, usually from a central location, as opposed to outside sales which engage in more traditional face-to-face selling (Gessner, 2009; Rapp et al., 2012). Finally, we note the lack of academic studies that measure performance based on the progress of leads in the sales pipeline, a concept that is essential in Inside Sales.

To address these gaps in the sales literature, we formulate our research question as: ***What are the drivers of team performance in B2B Inside Sales?*** Accordingly, the ***objectives*** of this study are: **(**1) to conceptualize the drivers of team-based B2B sales by synthesizing existing knowledge through a scoping review; (2) to identify different stages of the sales pipeline and formalize the performance of sales teams at each stage; and (3) to empirically test the impact of the drivers identified from the literature on team performance at each stage.

To narrow down our target population, we focus on users of Lead Management Systems (LMSs). There is a large variance of performance between teams using LMSs, making them an ideal segment for our study to understand the drivers of team-based selling (Reimann et al., 2009; Zablah et al., 2004). Furthermore, we focus our study on the B2B sector of the Insurance and Marketing & Advertising industries. Although both B2B and business-to-consumer (B2C) sectors use LMSs, the B2C sector does not emphasize account-based selling as much as much as the B2B sector does, hence every B2B sales lead is highly valuable (Kumar, 2012; Moore et al., 2015).

The remainder of this paper is organized as follows. First, we discuss the inside sales team selling background and conceptualization of our predictor and outcome variables, and how they form the hypothesized model. Then, we discuss the data, method and empirical model validation procedure used in this research. We then discuss and analyze the results across the tree stages of the sale pipeline. We conclude the paper with a discussion of the study's implications and contributions to research and practice.

5.2.Research Background and Conceptual Model

5.2.1. Customer Acquisition Process and Sales Performance Outcomes

The sales pipeline divides the customer acquisition process into multiple stages (Ang & Buttle, 2006; Patterson, 2007). Smith et al. (2006) propose the following three-stage model of the sales process: (1) lead generation, (2) conversion of leads into sales appointments, (3) and conversion of appointments into sales. A sales lead is an element of a target market who has signalled interest in a product (Carroll, 2006). Jaramillo and Marshall (2004) propose the same three stages, but introduce a prospecting stage between Stages 1 and 2. D'Haen and Van den Poel (2013) classify a sales process into four stages: (1) suspects, (2) prospects, (3) leads and (4) customers, where any newly generated lead is classified as a suspect irrespective of its quality. In our research, we adopt this classification but substitute the term "lead" with "qualified lead". This is because the sales pipeline describes the journey of a lead, therefore "lead" cannot itself be the label of one of the stages of that journey. After juxtaposing various stages of a lead progression from the literature, we obtain a total of four distinct stages of a lead as it moves along the sales pipeline: *Suspect*, *Prospect*, *Qualified Lead*, and *Client*.

Consolidating the definitions from the literature, we define the four stages as follows:

- A *suspect* is a new lead entered into the organizational LMS but has not been contacted yet.
- A *prospect* is a lead that has been contacted but has not yet been qualified yet to find out if it has the budget, decision-making authority, time and need for the product.
- A lead is a *qualified lead* when an appropriate fit has been determined and an appointment or further meeting is established with the decision maker where a final sales pitch occurs.
- If a lead agrees to buy, it becomes a *client*.

Furthermore, a lead can be classified as *won*, *lost* or *cancelled* (Virtanen et al., 2015). The classifications *won* and *lost* apply to the last (i.e., closing) stage, where the lead is either won and becomes a *client*, or is lost because the salesperson failed to close the deal. The classification *cancelled* means that the lead never made it to the final stage. A lead can be cancelled because of a loss of interest, an insurmountable obstacle or a difference that hinders progression, or simply a loss of contact. The classification of a lead as *lost* can be extended to the earlier stages as well, in which case it would mean *cancelled*. Thus, considering an outcome as a change of status, every stage can have two outcomes, "*won*" or "*lost*", where *won* means progress and *lost* means cessation of progress. Depending on how many stages a lead goes through in the pipeline, one can calculate the conversion (i.e., "won") ratio of each stage to measure the progress of that lead. We use quantifiable sales conversions as a performance measure at each stage of the sales pipeline. Indeed, several studies suggested such a measure for sales performance because of its objectivity (Ahearne et al., 2004; Yan et al., 2015). In a study involving sales executives, the introduction of new accounts for products and the closing ratio were listed as sales performance measures under externally oriented (i.e., marketplace) metrics (Zallocco et al., 2009). Both sales outcomes measures are highly objective as they depend on the successful acquisition of a customer. In this research, we use both measures via the total number of successful conversions at each stage and the performance ratio of each stage respectively.

5.2.2. Conceptual Model and Hypotheses

The predictors of team-based sales performance are numerous and diverse. But as justified earlier, we limited our literature search criteria to the characteristics of the teams and their interactions with LMSs. Note that LMS software has inundated the sales and marketing departments across industries (Ahearne et al., 2008), and it has experienced a tremendous uptake in Inside Sales (Magnotta, 2018; Martin, 2013).

Furthermore, because the outcome of the study is defined as quantifiable conversions of sales leads, the same objective rigor is applied to the selection of applicable predictors. Hence any predictors that require subjective assessment are ruled out. These include all behavior-based constructs at the individual level such as leadership, personality and orientation, and at the team level such as team potency, team cohesiveness and team identification.

Using a scoping literature review, we identified two main categories of factors which can impact team-based Inside Sales performance and can be objectively measured: (1) *Team Composition* which informs on team design; and (2) *Team Dynamics* which informs on the interactions of team members. Although this study was conducted using B2B data, we use “Inside Sales” and “B2B Inside Sales” interchangeably.

Our conceptual model (see Figure 5.1) proposes that *Team Composition* (i.e., Team size, Team experience, and Team specialization), and *Team Dynamics* (i.e., Task effort, Task input, Repetition, Team goal monitoring and Intra-team communication) lead to greater sales performance at three distinct stages of the sales pipeline through performance ratios (i.e., the suspect ratio, prospect ratio and qualification ratio). The model’s constructs are described below.

Figure 5.1 appears here

Team Composition

Within *Team Composition,* we identified three main factors that could influence B2B team-based sales performance: team size, team experience, and team specialization. All these factors should help to answer the question how to form the team to increase performance.

Team Size: Team size represents the number of members in each team. The members of a sales team can be put together temporarily depending on the needs of the buyers (Rapp, 1989). Hence, a team's size can fluctuate over the course of its existence, depending on whether new members are added or removed for new projects or new sets of leads.

Research findings on the effect of team size on sales performance are inconsistent. Arguing against bigger teams, Gooding and Wagner III (1985) stated that the size of a subunit in an organization is negatively correlated or not correlated at all with performance due to process losses and free rider effects. Mullen et al. (1989) claimed that larger group sizes lead to increased dissatisfaction among group members because of greater formalized structures. Perry et al. (1999) stated that evidence points to a drop of effective communication within bigger teams. On the other hand, arguing for bigger teams, Magjuka and Baldwin (1991) posited that while designing and administering employee involvement programs, team size has a positive impact on team performance. Larger teams are said to perform better due to greater access to information. Yetton and Bottger (1982) found bigger teams to be better decision makers by means of the best member strategy, whereby having more members increases the likelihood that a single member of the team comes up with the best decision that results in higher performance. Thus we see evidence for both larger and smaller teams leading to greater performance. However, the evidence seems to be slightly tilted towards smaller teams. Stewart (2006) confirmed this as he found team size to be negatively related to production teams, which are similar to Inside Sales teams, both having greater autonomy resulting from their interdependence and well-defined tasks. In light of this, we posit:

H1: Inside Sales teams of smaller size perform better at various stages of the sales pipeline.

Team Experience: Weinstein and Mullins (2012) defined team experience as the synthesis of each member's experience in a team, where experience is the knowledge gained during the length of service over the whole career of each team member. Mintu-Wimsatt and Gassenheimer (2000) and Rapp et al. (2010) constrained the boundaries of such definition to the length of service of each team member in the current position. We adopt the latter definition in our study because our data does not contain records of salespeople's experience outside the context of their current organization.

To relate team experience to sales performance, Delmar and Shane (2006) state that greater team experience leads to higher sales performance in new ventures, albeit the effect is non-linear and varies with the age of the venture. According to Cespedes (1992), a team is composed of multiple salespersons, and salesperson experience is identified as one of the contributors to greater sales performance via coordination. Other scholars confirm that salesperson experience leads to greater sales performance via salesperson behavior (Park & Holloway, 2003; Rapp et al., 2006). Hence, we posit that:

***H2: Inside Sales teams with more experience perform better at various stages of the sales pipeline*.**

Team Specialization: We define team specialization as the number of specialized roles in a team, where one member is solely responsible for performing one specialized task. Specificity of role is a strong antecedent to task interdependence, which is defined as the extent to which salespeople depend on one another for information and assistance to accomplish their tasks and improve their performance (Thompson, 2003). Hence, the greater the specificity of roles within a team, the more specialized that team is.

According to Yilmaz and Hunt (2001), task interdependence is a highly explanatory antecedent of salespeople's cooperative or coordinative behavior by way of task characteristics. The specificity of role (i.e., team specialization) requires the existence of such coordination. This linkage between the two concepts is corroborated by Dickinson and McIntyre (1997). Therefore, specialization is a key component of intra-team coordination in that each team member is specialized enough where they stand to profit from coordination. This leads to better sales performance via intra-team coordination. Hence, we posit that:

H3: Inside Sales teams with more specialized roles perform better at various stages of the sales pipeline.

Team Dynamics

Within *Team Dynamics,* we identified five factors that could influence B2B team-based sales performance: team effort, task input, repetition, team goal monitoring, and intra-team communication.

Team Effort: To the best of our knowledge, team effort has not been defined in prior literature, but individual salesperson's effort has been defined as the force, energy or activity with which work related tasks are accomplished (Brown & Peterson, 1994). Effort has also been described as the persistency of salespeople in terms of length of time committed to work despite failure (Sujan et al., 1994). Therefore, team effort denotes the force or energy with which teams carry out work related tasks, such as calling sales leads.

Effort explains the variance of sales performance in teams (Hunter & Perreault Jr, 2007; Perry et al., 1999). Selling effort also mediates the relationship between sales team connectedness and performance (Nowlin et al., 2019). Moreover, it is found to mediate the relationship between group goal setting and performance (Guzzo & Dickson, 1996). Therefore, effort is a contributor to greater performance. In addition, there is a link between a team's learning effort and sales performance, where team members make a concerted effort to learn new skills in the environment that they operate in (Jones et al. (2005). All these factors point to effort having a positive effect on sales performance either via learning, goal setting or team connectedness. So we posit that:

H4: Inside Sales teams with greater effort perform better at various stages of the sales pipeline.

Task Input: Barry and Stewart (1997) defined task input as fulfilling any responsibility towards achieving a certain goal. Team related research has expounded task input and socioemotional input as moderators of team performance. While measuring socioemotional input is beyond the scope of this study, we can measure task input in LMS usage, which could affect sales performance.

Task product must be specified before information cues can be recognized as task input (Wood, 1986). In our case, task product is the set of attributes that make up the functionalities of the LMS. An LMS records information that can act as task input. Another component of task input is task characteristic, which is defined as a composition of "key components of what the selling team must do and how the selling team must do it" (Perry et al., 1999, p. 43). Therefore, task input can be said to have two components, one is merely the doing of a task, the other assesses how well or how thoroughly a task has been done.

From a sales point of view, the input of data by salespeople is essential for clarifying the selling or buying situation (Tanner et al., 2005). Such input of data is a task by itself, and it has an effect on sales performance via collaboration. Steiner (1978) corroborated the necessity of task input, highlighting its importance in a team-based setting for the successful completion of goals. Hence, we are inclined to say that greater task input leads to better sales performance. The quality of such task input can be a moderator for outcomes in group processes (Gist et al., 1987). Proper fulfillment of tasks is a powerful mechanism to achieve sales performance via cooperation (Ahearne et al., 2008; Yilmaz & Hunt, 2001). Therefore, we posit that:

H5: Inside Sales teams with greater task input perform better at various stages of the sales pipeline.

Repetition: The concept of repetition is close to a transactive memory system. Bachrach et al. (2016) proposed that a transactive memory system mediates the relationship between effort or commitment and sales performance. In such a system, members of a team gain efficiency by repeatedly performing a task and engaging with other team members. Hence, we define repetition as the iteration of sets by team members, where each set is a unique combination of working roles of team members, each team member being responsible for one or more roles. Lewis (2003) uses specialized knowledge of team members and the repeated integration of expertise of different team members in different areas to measure transactive memory systems. We can thus infer that in order for coordination to work, it needs the repetition of specialization where team members repeat their roles in order to achieve greater efficiency.

Salespeople can become adept at using effective sales technology to execute tasks by means of repetition. The effective and habitual use of sales technology has facilitated collaboration amongst salespeople (Rodriguez & Honeycutt, 2011). This helps them to collaborate with colleagues and managers irrespective of where they are situated. Coordination is a huge subpart of collaboration, whereby the efforts of salespeople are coordinated among themselves, with other departments in the firm, and with stakeholders outside the firm (Tanner et al., 2005). Such a repetitive system of coordination enables the co-creation of new knowledge that is instrumental in achieving the company's objectives (Plouffe et al., 2004). Hence, repetition is an important gauge of intra-team coordination, leading to a better sales performance. We posit that:

H6: Inside Sales teams with greater repetition perform better at various stages of the sales pipeline.

Team Goal Monitoring: Bachrach et al. (2016, p. 9) defined team goal monitoring as the facilitation of auxiliary corroboration to ensure that "critical market focused processes are activated and performance criteria are met". Marks et al. (2001) concurred that team goal monitoring is a process by which members of a team track progress towards the accomplishment of goals.

In relation to sales performance, Bachrach et al. (2016) found that team goal monitoring leads to higher sales performance via commitment to service quality. Team goal monitoring also moderates the effect of team efficacy on sales team performance (Rapp et al., 2014). So we are inclined to say that greater team goal monitoring leads to better sales performance. We posit that:

H7: Inside Sales teams with more team goal monitoring perform better at various stages of the sales pipeline.

Intra-team Communication: Intra-team or within-team communication is defined by Guzzo and Shea (1992) as the social interaction between team members regarding how decisional and affective information is exchanged. Rajagopal (2008) measured team coordination as communication and flow of directives between salespeople.

While Levine and Moreland (1990) found little evidence that within-team communication leads directly to productivity, they did find it to have a positive impact on cooperation amongst team members. They attested to more equal participation because of electronic communication. Thus, intra-team communication is also a vital component of intra-team coordination by which it can positively affect sales performance, because good coordination in the face of a continually changing workplace dynamics cannot happen without adequate communication between team members. One of the virtues of using LMSs is the benefit of virtual communication. The right team members, regardless of geographical barriers, are able to better collaborate in order to accomplish relevant tasks and goals (Griffith & Dunham, 2014). Kiesler and Sproull (1992) found that computer usage leads to more open and direct communication, which results in more equal participation by all group members, leading to greater productivity. Milam and Mary (1993) corroborated the increment of productivity in teams who use computer technology via increased participation and synergy. According to Lai and Gelb (2015) communication patterns of key sales accounts can be complicated depending on the team structure, and thus communication between team members is a critical success factor. So we posit that:

H8: Inside Sales teams with greater intra-team communication perform better at various stages of the sales pipeline.

5.3.Methodology

This study implements a quantitative approach using secondary data. In order to identify the stages of the sales pipeline (Objective 2), we rely on text mining using Latent Dirichlet Allocation (LDA) and Jenks Natural Breaks to identify different categories of sales success outcomes and discretize team performance at each stage into appropriate tiers. Subsequently, to empirically test the impact of various predictors on sales teams performance across the identified stages (Objective 3), we use multinomial regression.

5.3.1. Text Mining Analysis Procedure

To understand how sales teams classify the results of the calls they make, we explore the outcome of each call made to a lead. This allows us to identify the different states of a lead as it progresses through the sales pipeline. We use *topic categorization*, which involves identifying the main theme in a text by employing both semantic and relational algorithms (Fan et al., 2006). We work with a number of predefined concepts first through concept extraction. We identify these predefined concepts using *Leximancer*, a concept (topic) extraction tool (Smith, 2003) that uses a mix of semantic and relational algorithms to create concept maps. This tool has been validated by many studies (Nunez-Mir et al., 2016; Smith & Humphreys, 2006). Our topic categorization applies inductive identification of 'themes' through the observation of patterns, and follows an unsupervised ontology which formulates relationships and develops theory (Dann, 2010).

To validate these stages, we use *Latent Dirichlet Allocation (LDA)* as a topic modelling technique to extract concepts from the text. LDA generates topics not only through the co-occurrence of words but also through a semantic connection between words (Maier et al., 2018). LDA treats each document as a mixture of topics, and each topic as a mixture of words (Silge & Robinson, 2017).

Compared to other topic modelling techniques, LDA was found to be particularly adept at detecting multiple topics from lengthy documents (Lee et al., 2010; Maier et al., 2018). In our case, Result Code is a lengthy document consisting of hundreds of thousands of rows. We will adapt the LDA procedure by Blei et al. (2003).

After assigning each lead to a stage of the sales pipeline, we calculate the performance ratios of each team.

- Suspect Ratio for a team is calculated by dividing the number of leads in the Suspect stage by the number of leads in the Suspect and No Contact stages for that team.
- Prospect Ratio for a team is calculated by dividing the number of leads in the Prospect stage by the number of leads in the Prospect and No Contact stages for that team.
- Qualification Ratio for a team is calculated by dividing the number of qualified leads by the number of qualified and No Contact leads for that team.

5.3.2. Jenks Natural Breaks Clustering

Having calculated the performance ratios from the identified stages of the sales pipeline; the next phase is to identify the outcome variables. These variables measure different levels of team performance based on the discretization of performance ratios at each stage of the sales pipeline. Once all teams and their performance ratios are listed, our aim is to discretize the continuous ratio variables into distinct groups. Therefore, we need to determine the cut-off points in the data to classify these groups. While a lot of discretization happens on the basis of equal length of groups over a certain range of data, or groups demarcated on a certain quartile or percentage of the data, we are more interested in identifying the natural breaks (if any) in the data. So instead of dividing the data into equal parts or choosing certain percentiles to divide it, we will divide our data by looking at the densities of the observations. To do this, we use Jenks Natural Breaks, a non-hierarchical iterative partitioning method for dividing observations into a pre-determined number of clusters. The method finds the natural breaks in the data by minimizing within-class variance, while maximising between class variance (Jenks, 1963). Non-hierarchical methods such as K-means clustering are better than their hierarchical counterparts as they are robust to outliers and heavily skewed distributions (Slater & Olson, 2001). But while K-means clustering is traditionally a multivariate technique, Jenks Natural Breaks clustering is suitable for classifying one-dimensional data while retaining the non-hierarchical attributes.

5.3.3. Model Selection and Validation Procedure

We employ multinomial logistic regression to operationalize and validate our model. Multinomial logistic regression is applicable when the dependent variable is categorical with more than two levels, as it is in our case. After the identification of the three categories of performance for the Suspect, Prospect and Qualification ratios, we run a multinomial logistic regression model for each ratio that comprises the eight predictor variables and the three outcome variables. For each hypothesis, we verify if the proposed relationship between the predictor variable and outcome variables is significant in terms of direction and effect. The low performance group is the designated baseline comparison group. The relative probability of a team being in the medium and high-performance groups has to be significant for each predictor variable in order to prove the respective hypothesis.

We check for overall model fit via a chi-square likelihood ratio test at a 0.05 confidence level and the Pseudo R-Squared values. In particular, we look at the McFadden R-Squared because it satisfies almost all criteria for running multiple logistic regressions together in a multinomial setting (Menard, 2000). A value between 0.20 and 0.40 exemplifies an excellent fit (McFadden, 1973). From the classification table, we obtain the accuracy of the models in predicting the outcome performance group. We look at the Akaike information criterion (AIC) values to see if a balance could be struck between goodness of fit and parsimony. Finally, to validate our findings, we employ bootstrapping where the data is repeatedly sampled using replacements from the original dataset.

5.4.Analysis and Results

5.4.1. Data

Data for this study was made available to us by a leading LMS software company with offices in Canada and the USA. The sample consisted of six B2B companies employing teams that used their LMS software in Inside Sales operations from 2005 to 2016. Three of these companies were from the Insurance Industry and three from the Marketing & Advertising Industry. Although our focus on two industries limits our scope of interpretability, it increases the external validity of the study for those two industries. Companies generate leads for their sales operations and interact with these leads as a part of their sales process which involves multiple acts such as inputting data, updating data, making calls, etc. all of which can be captured by LMSs. Table 5.1 shows the description of data fields collected for this research.

Table 5.1 appears here

To classify the stages of the sales pipeline using text mining, we relied on 4236 unique Result Codes used by teams from the 6 companies. The Result Codes field consists of codes for different Result IDs. A Result ID uniquely identifies the outcome of each call made to a lead. Our raw data consisted of over three million interactions of sales teams with sales leads as recorded in the LMSs of the 6 companies in our sample. There were 4236 sales teams and 929,481 sales leads in total. We extracted 8 predictor variables from the interactions. Our control variable is industry. We cleaned the data by calculating all our predictor variables on a per lead basis. Table 5.2 summarize the measures of each of our predictor variables as derived from the dataset.

Table 5.2 appears here

5.4.2. Elicitation of the Five Stages of the Sales Pipeline Using Text Mining

We were able to extract the five stages a lead goes through during its journey in the sales pipeline, namely *No Contact*, *Suspect*, *Prospect*, *Qualified lead* and *Client*. Running Leximancer yielded 63 concepts as indicated by our initial textual exploration of the data. We then used the LDA's bag-of-words method since it is better for short texts. LDA has the capability to generate enough relevant concepts whereby we can strengthen the definitions of our five stages. It also sheds light on the unassignable concepts to see if they can be stowed in a new category or fit within an existing category. We ran LDA modelling in R (Version 3.5.3). We first pre-processed the text by removing punctuation, stop words and whitespaces. We then plotted a perplexity chart to determine the optimum number of concepts by comparing models with different numbers of topics (see Figure 5.2). Perplexity is a statistical measure of how well a probability model predicts a sample. Perplexity was lowest at 203 topics hence we ran an LDA model using 203 topics. The 203 generated topics and the top five words of each topic per topic distribution are shown in Figure 5.2. The keywords are binned into the five identified categories (see Table 5.3).

Figure 5.2 appears here

Table 5.3 appears here

Next, we manually coded the result codes into one of the five stages. Manual coding after topic modelling is commonly used (Chuang et al., 2015; Jacobi et al., 2016). We had a clear indication of how the five stages differ from each other based on the literature, expert opinion and based on the topics we obtained from Leximancer and LDA. We were able to classify 4,302 unique result codes out of 4,326 (99.45%).

Throughout each lead's (Contact ID) interaction history (record of call history IDs) with the sales team, each lead can be classified into one or more of the five stages we have identified thus far. However, to measure team performance, the lead will be categorized in the last chronological stage out of the five possible stages. This will let us know the final highest outcome (i.e., final stage) of that lead for that team. Table 5.4 shows a distribution of teams by the number of leads they had at each stage.

Table 5.4 appears here

For progression ratios, we considered the number of teams who had leads at a particular stage and all prior stages as well. The Client stage was not well represented - only nine teams that had leads in all five stages including Client (see Table 5.4). Hence, we combined Client and Qualified Lead and labeled them Qualified Lead. No Contact was an initial stage of each lead. To measure the reliability of our classification, we used the test-retest method where we assigned each sales result to one of the five identified stages at two different points of time. A correlation score of above 0.8 between the two classifications meant a good reliability (Vilagut, 2014). Our measurement process's criterion and construct validities are in line with the definitions of the five identified stages (see Section 2.1.).

5.4.3. Determining the Performance Ratios

A team's Suspect Ratio, Prospect Ratio and Qualification Ratio were calculated by dividing the number of leads per team in each stage by the sum of leads in each stage and the No Contact stage. The average suspect, prospect and qualification rate for all teams were 43.7 %, 26.6% and 17.9% respectively.

There were 3,736 teams for which we had suspect ratios, 2,263 teams for which we had prospect ratios, and 1,762 teams for which we had qualification ratios. Next, we applied Jenks Natural Breaks to these ratios to find the natural break points whereby we could classify the teams for each ratio into groups. Each ratio was discretized into two, three, four, five and six classes respectively (see Table 5.5).

Table 5.5 appears here

For all three ratios, we can see that there is a significant jump in the goodness of variance fit (GVF) for three classes compared to two. Thus, we segmented our outcome variables into the three groups: low performers, medium performers and high performers for each ratio (see Table 5.6). Thus, the categorization of teams provides a better representation of team performance with respect to each ratio. Trichotomizing continuous variables is preferred to dichotomizing them as it reduces loss of data due to the transformation process (Gelman & Park, 2009).

Table 5.6 appears here

5.4.4. Model Evaluation

Even though our outcome variables are categorical in nature and have a tiered aspect to them where team performance increases from low to medium to high, we could not use ordinal regression on our data. This is because the groups did not meet the proportional odds assumption, which is a necessity for ordinal regression. For each ratio, the null hypothesis is rejected, the slope coefficients are the same across the three response categories.

Furthermore, Table 5.7 shows the likelihood ratio tests of each variable, and their collinearity diagnostics for the fit of the three models. Overall, the VIF values were checked for the Suspect, Prospect and Qualification ratios. None of them crossed the threshold of 10 as predetermined earlier. Also, none of the full factorial models for Suspect, Prospect and Outcome Ratios improved the model fit. Thus, each variable was uniquely important to the overall fit of the model. The AIC did improve without some of the variables, but the improvement was non-significant. Furthermore, with only nine variables, all of which are relevant for capturing team characteristics or interaction with sales leads, sacrificing fit for parsimony did not make sense.

Table 5.7 appears here

Table 5.8 shows the classification accuracy for each stage. All three models were found to be statistically significant at 0.05. Table 5.9 shows the parameter estimates for the medium and high performing teams in reference to the baseline low performing teams. The suspect ratio model was the least performing of the three models. Although most variables in the suspect ratio model were significant, with the exception of team experience and industry, the suspect ratio model performance was low with a McFadden pseudo R square value of 0.088 and low predictive performance with a 58.6% classification rate.

Table 5.8 appears here

The prospect ratio model was the best performing model out of the three. With the exception of industry, all other variables were significant in the prospect ratio model, and the model achieved an 87.2% classification rate and a McFadden pseudo R square of 0.499. The qualification ratio model was the second-best performing model out of the three. With the exception of specificity of role and industry, all other variables' qualification ratio model was significant. The qualification ratio model achieved an 83.3% classification rate and a McFadden pseudo R square of 0.362. The above information is further captured in Table 5.10 where green and red arrows indicate positive and negative significance respectively.

Table 5.9 appears here

Bootstrapping was performed using 1000 subsamples at the 95% confidence interval. Refer to Table 5.9 for the parameter estimates and degree of significance of the variables. The significance of the variables for the Prospect Ratio Model remains unchanged. For the Suspect Ratio Model, team size was found to be insignificant for medium performers. But Specificity of Role was found to be significant for high performers, which wasn't the case pre bootstrapping. For the Qualification Ratio model, Task Input and Repetition were found to be insignificant for high performers, but Specificity of Role was found to be significant, which was not the case pre bootstrapping. In all three stages there were no cases where the results for medium and high performing groups were overturned.

Table 5.10 appears here

5.5. Discussion and Implications

5.5.1. Discussion

Team Size Matters: There was enough evidence from the literature to make a case for both bigger and smaller team sizes increasing team performance. From H1, we see that to be a medium performing team, bigger teams were better at converting suspects, but smaller teams were better at converting prospects and qualifying leads. This makes sense, as one would want more team members for lower skilled jobs such as suspecting, compared to prospecting and qualifying which require more skills that cannot be substituted by assigning more team members. However, to be a high performing team, a smaller team size was the way to go throughout all stages of the sales pipeline (i.e., suspecting, prospecting and qualifying).

There is no Substitute for Team Effort and Intra-team Communication in Team Dynamics: Except for team size, all other predictor variables were hypothesized to have a positive effect on team performance. However, apart from Team Effort and Intra-Team Communication, the six other predictor variables had at least one instance of significant negative effect on either the suspect, prospect or qualification models. Such a pattern manifested itself through the differences between the lower and higher stages of the sales pipeline. But Team Effort and Team Communication had a positive impact on all three performance ratios, which is a testament to the positive role they play in Team Dynamics.

***More skills and customization are required in the later stages of the sales pipeline*:** We found that less task input is better for the suspecting and prospecting stages, but more task input is better for the qualifying stage. This alludes to the increment in skill levels as one moves along the sales pipeline. For suspecting and prospecting, inputting comments into the LMS may take away from the time and effort needed to make calls, which are key for succeeding in those stages. As for qualification, mere effort is not enough, and one has to diligently perform other duties such as inputting content into the LMS. The reverse is true for repetition, where we found that more repetition is important in the suspecting stage for medium and high performing teams, but not for the qualifying stage. This may suggest that while repetition of duties maintains the same structure of the team, it is important at the earlier stages of the sales pipeline, but a hindrance at the later stages which require more customization.

Similarly, the same can be said of Team Goal Monitoring, where in order to be a medium or high performing team, you need less Team Goal Monitoring for suspecting, but more for prospecting and qualifying. Therefore, monitoring the progress of goals takes away from effort in suspecting, but it is important at the prospecting and qualification stages, where a salesperson needs knowledge about the state of the lead.

Team Experience can be a substitute for skills when it comes to Team Composition: We found that to be a medium performing team, team experience is not significant for suspecting and prospecting, but it is for qualification. This shows that for tasks requiring more skills, teams would need more experience, whereas for lower level tasks, experience would not make a difference. Such a contrast is more apparent when looking at high performing teams, as experience was found to be significant for all three stages, but teams with less experience fared better at suspecting while teams with more experience fared better at prospecting and qualifying.

Leads Reach a Peak and stop progressing: Although the literature suggests that leads progress from one stage to another through the sales pipeline, we found that most of the teams reached the maximum stage with their leads at the initial series of interactions and did not progress further. If we look at the history of all leads, we see that they are extremely "sticky" as they tend to stay in one stage during their entire lifecycle or move from No Contact to just one other stage. Therefore, there is not a lot of progression where leads move from stage to stage, but rather the salesperson has one shot to move the lead from No Contact to the highest stage possible. Accordingly, we argue that a B2B sale teams should try to reach the maximum from the initial stages of their interaction with a lead, otherwise the chances to progress later through the pipeline are rather weak.

5.5.2. Contributions to Research

Even though other studies have focused on individual salespersons' factors to measure sales performance, it remains to be seen if those factors can be aggregated at a team level to measure sales performance (Verbeke et al., 2011). Our study addresses this issue by conceptualizing and empirically validating team-based predictors of team-based B2B sales performance. This is what we achieved by developing a conceptual model that considers Team Composition factors and Team Dynamics factors.

Moreover, the advent of sales technology has placed increased demands on companies to employ teams capable of maximizing the efficiency of sales technology use (Devine et al., 1999; Rangarajan et al., 2005). The computerization of the workplace has meant the "expansion of research on groups that use computers in their work" (Guzzo & Dickson, 1996, p. 320). Indeed, constructs that we used to measure group size are the result of interactions with the LMS used by the company that provided our dataset. This study confirms the positive effect of sales technology acceptance and use on sales performance, which has been validated in the literature (Ahearne et al., 2004; Hunter & Perreault, 2006). Because the measurement of every construct except team size was dependent on salespeople's use of sales technology, proven hypotheses not only indicate the existence of the proposed relationships but also the validity of sales technology use overall.

The novelty of our research is twofold. First, to the best of our knowledge, our study is the only one that measures B2B team sales performance at multiple levels of the sales pipeline. Although there were studies modelling and assessing the impacts of different variables on sales performance (e.g., Gessner & Scott, 2009; Virtanen et al., 2015), there have been no attempts to assess sales performance at specific stages of the sales pipeline. By segmenting the stages of the sales pipeline, we monitored the performance of sales teams at distinct points of a lead's journey from the time it enters the sales pipeline to the time it becomes a client or falls out of the pipeline.

Second, most previous studies exploring sales performance relied on survey data. The survey method has many drawbacks, including self-selection, acquiescence, extremity and other biases (Zikmund et al., 2013). Our study relies exclusively on secondary data in the form of records of companies from multiple industries interacting with sales leads. Our dataset includes 929481 records captured by an LMS in the act of sales teams performing their sales duties.

5.5.3. Implications for Practitioners

This study contributes to the field of industrial marketing management through an understanding of what makes sales teams successful based on Team composition and Team Dynamics (i.e., the nature of teams and how they interact with sales leads). Due to the increased operational cost of maintaining an external sales force, team-based Inside Sales have gained prominence especially when supported by data analytics (Gessner & Scott, 2009). Using various analytical methods, this study built predictive models considering team composition and team dynamics factors that can be improved for a greater sales performance. Our models facilitate the comprehension of the important success factors by which managers can strategize their sales process. According to (Avlonitis & Panagopoulos, 2010), empirical studies on the engineering of the sales process provide salespeople with the insights to better suspect, prospect and qualify leads.

Even though it is hard to predict successful suspecting, compared to prospecting and qualifying, sales managers can benefit from knowing that it is more about effort (e.g., volume of calls) and less about checking progress or completing specific tasks (e.g., inputting a comment in the LMS). Moreover, from a sale management viewpoint, prospecting and qualifying leads are more crucial for prediction.

An interesting insight from our research is that while inputting comments has a negative impact on prospecting and suspecting, checking progress has a positive effect on prospecting. In fact, team goal monitoring via checking progress and intra-team communication are the strongest predictors of successful prospecting. Thus, team goal monitoring may be seen as a more advanced skill than inputting comments. Moreover, task input, intra-team communication and team experience are the strongest predictors of qualification. But repetition has a negative effect on qualification, which is not the case for suspecting and prospecting. Based on these insights, sales managers can allocate different teams to different tasks. More experienced members who have a more customized approach to each lead would perform the qualifying, whereas less experienced members who have a less customized approach of dealing with leads would be in charge of suspecting and prospecting.

5.6.Limitations

Our study carries three key limitations. First, the use of secondary data also has drawbacks. Some relevant team constructs for exploring B2B team sales performance can only be considered by future studies that use primary data. For instance, the personalities and other individual characteristics of team members including leadership could help us understand what affects performance beyond favorable team composition and dynamics. Hence, we call on future studies to explore data sources that capture salespeople's personal trails. Second, we limited our study to two industries (i.e., Insurance and Marketing & Advertising). For future studies, it would be better if more industries from the B2B sector are considered. Finally, it is always a daunting task to come up with measures that fully encapsulate respective constructs. Especially for the reflective variables of team dynamics, we are heavily dependent on input recorded in the LMS. Team dynamics here is restricted to the team members dynamism within the scope of the LMS. We call on future research to consider alternative measures that are broader.

Table 5.1: Data field Description

Data Field	Description
AddUserID	ID of the salesperson who added the lead to the list
ContactOwnerGroupID	Refers to the sales team that a lead is assigned to
UpdateUserID	The ID of the salesperson who last updated the call data of the lead
UserID	The ID of the salesperson who called the lead
CallDate	The date of the contact made with a lead
CallHistoryIDs	The ID of each call interaction with a lead
LeadStatus	Refers to the name and description of the status or position of a lead in its journey through the sales pipeline
UserStartDate	The date the salesperson's account was created in the system
Comments	Remarks about the outcome of the interaction of contact attempt with the lead

Table 5.2: Predictor Variables Description and Measures

Variable	Description	Data Fields Measures	Scale
Team Size	Number of team members in each team (Gooding & Wagner III, 1985; Stewart, 2006)	The number of distinct Salesperson IDs (i.e., AddUserID, UpdateUserID and UserID) for interaction history with a lead.	Numeric (3-35)
Team Experience	The duration of each team member's stay in the organization (Mintu-Wimsatt & Gassenheimer, 2000; Rapp, Ahearne, Mathieu, & Rapp, 2010).	Difference of months between last call made (i.e., CallDate) and user account creation (i.e., UserStartDate). This figure is summed for all team members.	Numeric (0.5 to 79) Months
Team Specialization	The coordination within teams, which is dependent on everyone doing their part or being involved (Campion, Medsker, & Higgs, 1993; Yilmaz & Hunt, 2001)	The average number of user IDs in a team that serve only one role in the team's interaction with a lead. Different roles in this case constitute AddUserID, UserID and UpdateUserID.	Numeric (0 to 1.5)
Team Effort	Total number of calls made. (Brown & Peterson, 1994; Sujan, Weitz, & Kumar, 1994)	The number of calls (i.e., CallHistoryIDs) for each team (i.e., ContactOwnerGroupID) This figure is summed for all team members.	Numeric (0 to 53)
Task Input	Refers to the fulfillment of sales task each salesperson is responsible for with due diligence (Barry & Stewart, 1997) Includes "note taking" as a part of their archival IT use measures (Ahearne, Jones, Rapp, & Mathieu, 2008).	The number of content words of all call history comments made by a salesperson for each lead gives us the total task input for that lead. Subsequently average this number for all leads worked on by a team to ascertain the task input of that team.	Numeric (1 to 5)
Repetition	The perpetual continuity of work in a given role until expertise is achieved (Lewis, 2003).	The number of reiterations of sets in a team, for all leads worked on by a team. We count the number of sets per lead per team, where each set is a different combination of roles performed by those team members. We average this number for all the leads the team has worked on to arrive at the repetition of a team. Different roles in this case constitute AddUserID, UserID and UpdateUserID.	Numeric (0.01 to 240)
Team Goal Monitoring	Tracking progress towards a goal and monitoring the advancement towards a goal to measure team goal monitoring (Bachrach, Mullins, & Rapp, 2016; Marks, Mathieu, & Zaccaro, 2001)	The average number of lead status (i.e., LeadStatus) updates for each team.	Numeric (1 to 14)
Intra-team Communication	Refers to all signs of communication (e.g., directive language pertaining to feedback and any information regarding the business, such as product attributes, competitors and customers (Rajagopal & Rajagopal, 2008; Yilmaz & Hunt, 2001).	The number mentions of any content words in call history comments, and lead status, multiplied by the number of different distinct user IDs making those comments or updates.	Numeric (1 to 212)

Table 5.3: Result Codes -Identification of the Stages using LDA in R

No Contact	Suspect	Prospect	Qualified	Client
• Answering machine • Busy signal • Drop • Leave VM (voicemail) • Left message • Duplicate • Invalid • Unreachable • Skipped • Retry • Blind email	• Future prospect • Potential prospect • DNC (do not contact) • Number disconnected • Research • Corp handles • Unqualified • Unsuitable • Disqualified • Resigned • Currently satisfied • Refused • Research • Already engaged • No longer with company • Hung up • Screened • Using " " • Remove from list • Denied • Gatekeeper • Language barrier • Rejected • Blocked • Verify • Purchased recently • Enrolled to competitor • Deceased • Delete • Uninsurable	• Info requested • Cold • Refer • Rescheduled • Missed appointment • Wants " " • Interested • Needs confirmation • Yes • Expressed interest • Warm • Request for quote • Unhappy • Send whitepaper • Pitched • Verified • Progress • Drip • Pending • Dead • Fit • Nurture • Explain • Decision maker • Follow up • Positive	• Office webinar • Presented • Interview • Demo • Transferred • Appointment • Confirmed • Cancellation • Approved • Consultation • Registered • Scheduled presentation • Meeting • Lost • Set time • Hot lead • Opportunity • Declined • Completed survey • Closer	• Sale • Order placed • Deal • Won • Sold • Bought

Table 5.4: Distribution of Teams by the Final Outcome of the Lead

Stages	Count
No Contact	3957
No Contact + Suspect	3741
No Contact + Suspect + Prospect	1727
No Contact + Suspect + Prospect + Qualified	1207
No Contact + Suspect + Prospect + Qualified+ Client	9

Table 5.5: Goodness of Fit Test

Classes	Suspect Ratio	Prospect Ratio	Qualification Ratio
2	0.644	0.834	0.753
3	0.823	0.926	0.904
4	0.903	0.960	0.948
5	0.937	0.976	0.969
6	0.957	0.985	0.979

Table 5.6: Threshold Analysis

	Low	Medium	High
Qualification Ratio Classes	0 - 0.1853933	0.1853933 - 0.6086957	0.6086957 - 1
Prospect Ratio Classes	0 - 0.2361111	0.2361111 - 0.6513317	0.6513317 - 1
Suspect Ratio Classes	0 - 0.3248945	0.3248945 - 0.6308594	0.6308594 - 1

Table 5.7: Likelihood Ratio test

Predictor Variables	Suspect Ratio		Prospect Ratio		Qualification Ratio	
	VIF	AIC	VIF	AIC	VIF	AIC
Intercept		6822.06		1741.27		1572.79
Team Size	6.31*	6857.11	5.51*	1860.52	5.43*	1633.51
Team Experience	1.10ns	6822.71	1.10*	1759.15	1.15*	1599.94
Team Specialization	1.04**	6827.95	1.06**	1746.86	1.05ns	1574.37
Team Effort	2.8*	6933.44	2.68*	1799.58	2.49*	1625.86
Task Input	3.22**	6828.43	4.27*	1803.70	5.00*	1584.66
Repetition	1.10*	6898.48	1.28*	1788.21	1.24*	1587.62
Team Goal Monitoring	1.71**	6830.23	1.83*	2068.96	1.80*	1601.37
Intra-Team Communication	7.14*	6855.16	7.01*	1955.66	5.78*	1615.22
Industry	ns	6822.38	ns	1739.86	ns	1569.21

Significant at 1% = “*” and Significant at 5% = “**”

Table 5.8: Classification accuracy

Suspect Ratio Classification Table					Prospect Ratio Classification Table					Qualification Ratio Classification Table				
Observed	Predicted				Observed	Predicted				Observed	Predicted			
	1	2	3	Percent Correct		1	2	3	Percent Correct		1	2	3	Percent Correct
Low Performing Team	773	556	8	57.80%	Low Performing Team	1615	42	1	97.40%	Low Performing Team	1284	58	3	95.50%
Medium Performing Team	436	1388	33	74.70%	Medium Performing Team	107	263	33	65.30%	Medium Performing Team	157	145	8	46.80%
High Performing Team	97	415	30	5.50%	High Performing Team	45	62	95	47.00%	High Performing Team	41	27	39	36.40%
Overall %	35.00%	63.10%	1.90%	58.60%	Overall %	78.10%	16.20%	5.70%	87.20%	Overall %	84.10%	13.10%	2.80%	83.30%

Table 5.9: Model Estimate

	Predictor Variables	Suspect			Prospect			Qualification		
		β	SE	Wald	β	SE	Wald	β	SE	Wald
M	Intercept	2.05	1.22	2.83	1.92	1.62	1.41	-0.20	1.78	0.01
	Team Size	0.13**	0.06	4.60	-0.93*	0.10	90.74	-0.45*	0.08	34.76
	Team Experience	0.00ns	0.00	0.30	0.00ns	0.01	0.11	0.04*	0.01	23.97
	Team Specialization	-3.30**	1.17	7.96	-5.61*	1.59	12.40	-4.02**	1.72	5.48
	Team Effort	0.24*	0.05	24.60	0.28*	0.04	40.72	0.33*	0.04	58.20
	Task Input	-0.03ns	0.03	0.78	-0.17*	0.03	26.34	0.12*	0.03	15.42
	Repetition	0.13*	0.02	66.25	0.14*	0.03	31.11	-0.16*	0.05	9.31
	Team Goal Monitoring	-0.10ns	0.09	1.24	3.21*	0.27	145.70	0.19ns	0.10	3.63
	Intra-Team Communication	0.04**	0.02	3.78	0.22*	0.02	99.29	0.11*	0.02	29.38
	[Industry=Insurance]	-1.46ns	1.15	1.59	2.43**	1.25	3.79	-0.52ns	0.96	0.29
	[Industry=Marketing & Advertising]	0^b	.	.	0^b	.	.	0^b	.	.
	Intercept	1.37	1.57	0.76	-1.75	2.24	0.61	-0.82	2.29	0.13
H	Team Size	-0.24*	0.07	10.81	-1.00*	0.13	60.26	-1.02*	0.17	36.36
	Team Experience	-0.01**	0.01	4.53	0.06*	0.01	18.70	0.05*	0.01	17.84
	Team Specialization	-2.80ns	1.50	3.49	-3.97ns	2.13	3.49	-3.68ns	2.11	3.04
	Team Effort	0.55*	0.06	100.62	-0.19ns	0.10	3.63	0.25*	0.08	9.03
	Task Input	-0.12*	0.04	9.13	-0.33*	0.04	55.84	0.10**	0.04	6.30
	Repetition	0.08*	0.02	12.58	0.02ns	0.04	0.27	-0.36**	0.14	6.51
	Team Goal Monitoring	-0.40*	0.12	11.69	3.77*	0.30	159.25	0.94*	0.15	37.10
	Intra-Team Communication	0.14*	0.02	31.09	0.34*	0.03	141.91	0.17*	0.03	37.02
	[Industry=Insurance]	0.29ns	1.13	0.07	-14.53*	0.00	.	0.11ns	1.42	0.01
	[Industry=Marketing & Advertising]	0^b	.	.	0^b	.	.	0^b	.	.

Significant at 1% = “*” and Significant at 5% = “**”

Medium Performer = “M” and High Performer = “H”

Table 5.10: Significance Test

Hypotheses		Suspect Ratio	Validation	Prospect Ratio	Validation	Qualification Ratio	Validation
H1	Team Size (Medium Performer)	+	Rejected	-	Accepted	-	Accepted
	Team Size (High Performer)	-	Accepted	-	Accepted	-	Accepted
H2	Team Experience (Medium Performer)	Not-significant		Not-significant		+	Accepted
	Team Experience (High Performer)	-	Rejected	+	Accepted	+	Accepted
H3	Team Specialization (Medium Performer)	-	Rejected	-	Rejected	-	Rejected
	Team Specialization (High Performer)	Not-significant		Not-significant		Not-significant	
H4	Team Effort (Medium Performer)	+	Accepted	+	Accepted	+	Accepted
	Team Effort (High Performer)	+	Accepted	Not-significant		+	Accepted
H5	Task Input (Medium Performer)	Not-significant		-	Rejected	+	Accepted
	Task Input (High Performer)	-	Rejected	-	Rejected	+	Accepted
H6	Repetition (Medium Performer)	+	Accepted	+	Accepted	-	Rejected
	Repetition (High Performer)	+	Accepted	Not-significant		-	Rejected
H7	Team Goal Monitoring (Medium Performer)	Not-significant		+	Accepted	Not-significant	
	Team Goal Monitoring (High Performer)	-	Rejected	+	Accepted	+	Accepted
H8	Intra-team Communication (Medium Performer)	Not-significant		+	Accepted	+	Accepted
	Intra-team Communication (High Performer)	+	Accepted	+	Accepted	+	Accepted

Positive relationship = “+” and Negative Relationship = “-”

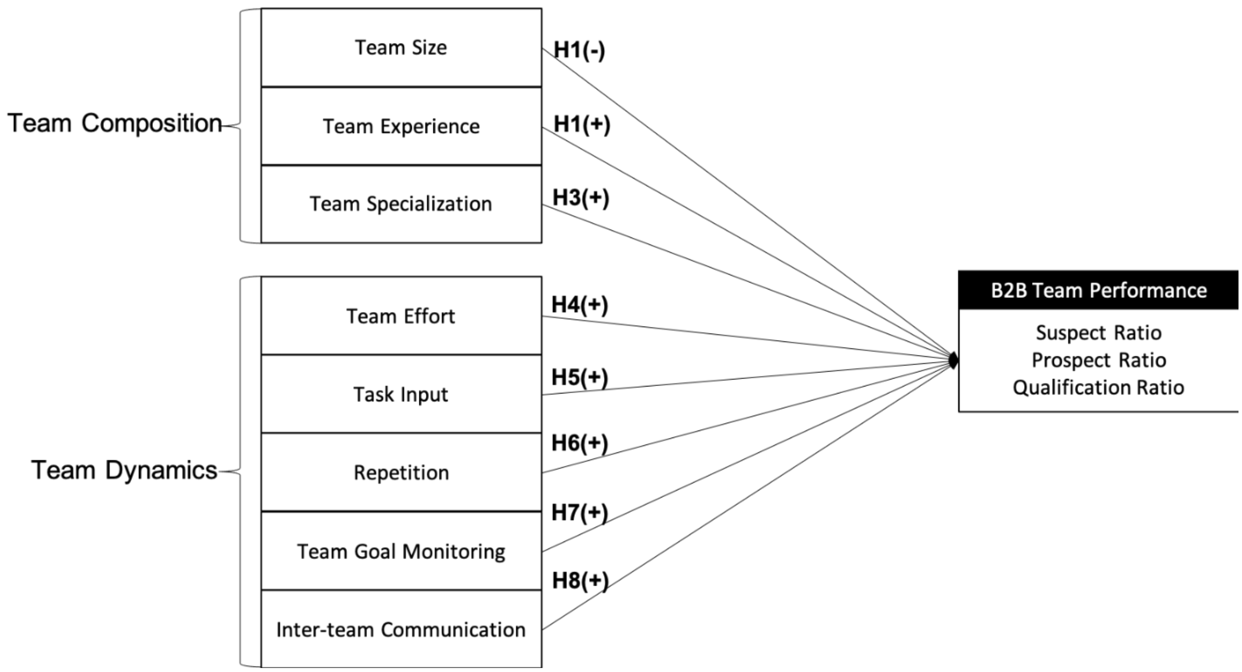

Figure 5.1: Drivers of Team-Based Performance in Inside Sales

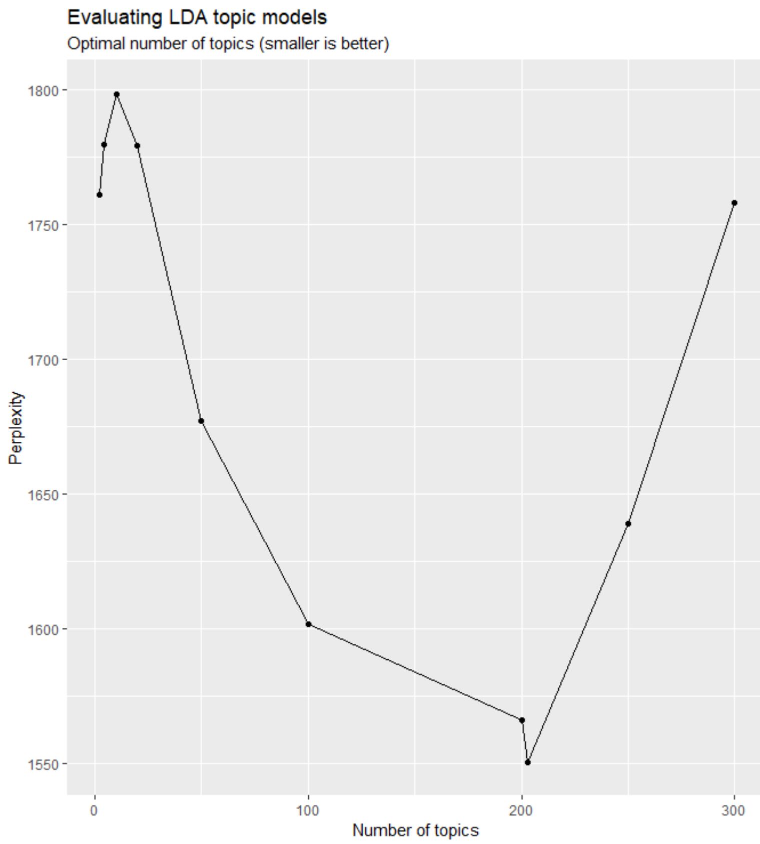

Figure 5.2: Optimal Number of LDA Topics

References

Adamson, B., Dixon, M., & Toman, N. (2014, 2014-01-09T19:00:53Z). Why Individuals No Longer Rule on Sales Teams. *Harvard Business Review.*

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*, 671-685.

Ahearne, M., Srinivasan, N., & Weinstein, L. (2004). Effect of Technology on Sales Performance: Progressing from Technology Acceptance to Technology Usage and Consequence. *Journal of Personal Selling & Sales Management, 24*, 297-310.

Ang, L., & Buttle, F. (2006). Managing For Successful Customer Acquisition: An Exploration. *Journal of Marketing Management, 22*(3-4), 295-317. doi:10.1362/026725706776861217

Avlonitis, G. J., & Panagopoulos, N. G. (2010). Selling and sales management: An introduction to the special section and recommendations on advancing the sales research agenda. *Industrial Marketing Management, 39*(7), 1045-1048. doi:10.1016/j.indmarman.2009.12.006

Bachrach, D. G., Mullins, R. R., & Rapp, A. A. (2016). Intangible sales team resources: Investing in team social capital and transactive memory for market-driven behaviors, norms and performance. *Industrial Marketing Management, 62*, 88-99. doi:10.1016/j.indmarman.2016.08.001

Barry, B., & Stewart, G. L. (1997). Composition, process, and performance in self-managed groups: The role of personality. *Journal of Applied Psychology, 82*(1), 62.

Batt, R. (1999). Work organization, technology, and performance in customer service and sales. *ILR Review, 52*(4), 539–564.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of machine Learning research, 3*(Jan), 993-1022.

Brown, S. P., & Peterson, R. A. (1994). The effect of effort on sales performance and job satisfaction. *Journal of marketing, 58*, 70.

Carboni, I., & Ehrlich, K. (2013). The Effect of Relational and Team Characteristics on Individual Performance: A Social Network Perspective. *Human Resource Management, 52*(4), 511-535. doi:10.1002/hrm.21539

Carroll, B. (2006). What's a Lead?: [1]. *Target Marketing; Philadelphia, 29*(11), 28-30,32-34.

Cespedes, F. V. (1992). Sales coordination: an exploratory study. *Journal of Personal Selling & Sales Management, 12*(3), 13–29.

Chuang, J., Roberts, M. E., Stewart, B. M., Weiss, R., Tingley, D., Grimmer, J., & Heer, J. (2015). *TopicCheck: Interactive alignment for assessing topic model stability.* Paper presented at the Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies.

Cummings, B. (2007). Group Dynamics. *Sales and Marketing Management; New York, 159*(1), 8.

D'Haen, J., & Van den Poel, D. (2013). Model-supported business-to-business prospect prediction based on an iterative customer acquisition framework. *Industrial Marketing Management, 42*(4), 544-551. doi:10.1016/j.indmarman.2013.03.006

Dann, S. (2010). Redefining social marketing with contemporary commercial definitions. *Journal of Business Research, 63*, 147-153. doi:10.1016/j.jbusres.2009.02.013

Delmar, F., & Shane, S. (2006). Does experience matter? The effect of founding team experience on the survival and sales of newly founded ventures. *Strategic Organization, 4*(3), 215-247. doi:10.1177/1476127006066596

Deloitte. (2016). Global Human Capital Trends 2016: The new organization-Different by design. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/global/Documents/HumanCapital/gx-dup-global-human-capital-trends-2016.pdf

Devine, D., Clayton, L., Philips, J., Dunford, B., & Melner, S. (1999). Teams in Organizations. *Small Group Research, 30*(6), 678-711. doi:10.1177/104649649903000602

Dickinson, T. L., & McIntyre, R. M. (1997). A conceptual framework for teamwork measurement. In *Team performance assessment and measurement: Theory, methods, and applications* (pp. 19-43). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.

Fan, W., Wallace, L., Rich, S., & Zhang, Z. (2006). Tapping the power of text mining. *Communications of the ACM, 49*(9), 76-82. doi:10.1145/1151030.1151032

Garrett, J., & Gopalakrishna, S. (2017). Sales team formation: The right team member helps performance. *Industrial Marketing Management*. doi:10.1016/j.indmarman.2017.06.007

Gelman, A., & Park, D. K. (2009). Splitting a Predictor at the Upper Quarter or Third and the Lower Quarter or Third. *The American Statistician, 63*(1), 1-8. doi:10.1198/tast.2009.0001

Gessner, G., & Scott, R. A. (2009). Using Business Intelligence Tools to Help Manage Costs and Effectiveness of Business-to-Business Inside-Sales Programs. *Information Systems Management, 26*(2), 199-208. doi:10.1080/10580530902797623

Gessner, G. a. (2009). Using Business Intelligence Tools to Help Manage Costs and Effectiveness of Business-to-Business Inside-Sales Programs. *Information Systems Management, 26*(2), 199. Retrieved from http://sfx.scholarsportal.info/ottawa?url

Gist, M. E., Locke, E. A., & Taylor, M. S. (1987). Organizational Behavior: Group Structure, Process, and Effectiveness. *Journal of Management, 13*(2), 237-257. doi:10.1177/014920638701300204

Gong. (2017). If You're Selling Alone, You're Doing It Wrong (These Stats Explain Why). Retrieved from https://www.gong.io/blog/team-selling/

Gooding, R. Z., & Wagner III, J. A. (1985). A Meta-Analytic Review of the Relationship between Size and Performance: The Productivity and Efficiency of Organizations and Their Subunits. *Administrative Science Quarterly, 30*(4), 462-481.

Griffith, B. A., & Dunham, E. B. (2014). *Working in Teams: Moving From High Potential to High Performance*. SAGE Publications: SAGE Publications.

Guzzo, R. A., & Dickson, M. W. (1996). Teams in organizations: Recent research on performance and effectiveness. *Annual Review of Psychology, 47*(1), 307–338.

Guzzo, R. A., & Shea, G. P. (1992). Group performance and intergroup relations in organizations. In *Handbook of industrial and organizational psychology, Vol. 3, 2nd ed* (pp. 269-313). Palo Alto, CA, US: Consulting Psychologists Press.

Hunter, G. K., & Perreault Jr, W. D. (2007). Making sales technology effective. *Journal of marketing, 71*(1), 16–34.

Hunter, G. K., & Perreault, W. D. (2006). Sales Technology Orientation, Information Effectiveness, and Sales Performance. *Journal of Personal Selling & Sales Management, 26*(2), 95-113. doi:10.2753/PSS0885-3134260201

Jacobi, C., van Atteveldt, W., & Welbers, K. (2016). Quantitative analysis of large amounts of journalistic texts using topic modelling. *Digital Journalism, 4*(1), 89-106. doi:10.1080/21670811.2015.1093271

Jaramillo, F., & Marshall, G. W. (2004). Critical success factors in the personal selling process: An empirical investigation of Ecuadorian salespeople in the banking industry. *International Journal of Bank Marketing, 22*, 9-25. doi:10.1108/02652320410514906

Jenks, G. (1963). Generalisation in Statistical Mapping. *Annals of the Association of American Geographers, 53*, 15-26. doi:10.1111/j.1467-8306.1963.tb00429.x

Jones, E., Dixon, A. L., Chonko, L. B., & Cannon, J. P. (2005). Key accounts and team selling: a review, framework, and research agenda. *Journal of Personal Selling & Sales Management, 25*(2), 181–198.

Kiesler, S., & Sproull, L. (1992). Group decision making and communication technology. *Organizational behavior and human decision processes, 52*(1), 96-123. doi:10.1016/0749-5978(92)90047-B

Kumar, V. (2012). *Customer Relationship Management : Concept, Strategy, and Tools* (2. ed. 2012. ed.). Berlin, Heidelberg: Berlin, Heidelberg : Springer Berlin Heidelberg : Imprint: Springer, 2012.

Lai, C. J., & Gelb, B. D. (2015). Key account teams: success factors for implementing strategy. *Journal of Business Strategy, 36*(4), 48-55. doi:10.1108/JBS-07-2014-0079

Lee, S., Song, J., & Kim, Y. (2010). An empirical comparison of four text mining methods. *Journal of Computer Information Systems, 51*(1), 1-10.

Levine, J. M., & Moreland, R. L. (1990). Progress in Small Group Research. *Annual Review of Psychology, 41*(1), 585-634. doi:10.1146/annurev.ps.41.020190.003101

Lewis, K. (2003). Measuring Transactive Memory Systems in the Field: Scale Development and Validation. *Journal of Applied Psychology, 88*(4), 587-604. doi:10.1037/0021-9010.88.4.587

Magjuka, R. J., & Baldwin, T. T. (1991). Team-Based Employee Involvement Programs: Effects of Design and Administration. *Personnel Psychology, 44*(4), 793-812. doi:10.1111/j.1744-6570.1991.tb00699.x

Magnotta, S. R. (2018). Can You Hear Me Now? An Innovative Experiential Learning Module to Prepare Tomorrow's Inside Salespeople. *Marketing Education Review, 28*(2), 75-79. doi:10.1080/10528008.2018.1464884

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., . . . Adam, S. (2018). Applying LDA Topic Modeling in Communication Research: Toward a Valid and Reliable Methodology. *Communication Methods and Measures, 12*(2-3), 93-118. doi:10.1080/19312458.2018.1430754

Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A Temporally Based Framework and Taxonomy of Team Processes. *Academy of Management Review, 26*(3), 356-376. doi:10.5465/amr.2001.4845785

Martin, S. W. (2013, 2013-11-04T18:00:09Z). The Trend that is Changing Sales. *Harvard Business Review*.

McFadden, D. L. (1973). Conditional Logit Analysis of Qualitative Choice Behavior. In *Frontiers in Econometrics*. New York: Wiley.

Menard, S. (2000). Coefficients of Determination for Multiple Logistic Regression Analysis. *The American Statistician, 54*(1), 17-24. doi:10.2307/2685605

Milam, A., & Mary, R. (1993). Using a Group Decision Support System For Creativity. *The Journal of Creative Behavior, 27*(1), 28-35. doi:10.1002/j.2162-6057.1993.tb01384.x

Mintu-Wimsatt, A., & Gassenheimer, J. B. (2000). The Moderating Effects of Cultural Context in Buyer-Seller Negotiation. *Journal of Personal Selling & Sales Management, 20*(1), 1-9. doi:10.1080/08853134.2000.10754215

Moon, M. A., & Armstrong, G. M. (1994). Selling teams: A conceptual framework and research agenda. *Journal of Personal Selling & Sales Management, 14*(1), 17–30.

Moore, J. N., Raymond, M. A., & Hopkins, C. D. (2015). Social Selling: A Comparison of Social Media Usage Across Process Stage, Markets, and Sales Job Functions. *Journal of Marketing Theory and Practice, 23*(1), 1-20. doi:10.1080/10696679.2015.980163

Mullen, B., Symons, C., Hu, L.-T., & Salas, E. (1989). Group size, leadership behavior, and subordinate satisfaction. *The journal of general psychology, 116*(2), 155-170.

Mullins, R. R., & Panagopoulos, N. G. (2019). Understanding the theory and practice of team selling: An introduction to the special section and recommendations on advancing sales team research. *Industrial Marketing Management, 77*, 1-3.

Nowlin, E. L., Walker, D., & Anaza, N. (2019). The Impact of Manager Likeability on Sales Performance. *Journal of Marketing Theory & Practice, 27*, 159-173. doi:10.1080/10696679.2019.1577684

Nunez-Mir, G. C., Iannone, B. V., Pijanowski, B. C., Kong, N., & Fei, S. (2016). Automated content analysis: addressing the big literature challenge in ecology and evolution. *Methods in Ecology and Evolution, 7*(11), 1262-1272. doi:10.1111/2041-210X.12602

Park, J.-E., & Holloway, B. B. (2003). Adaptive Selling Behavior Revisited: An Empirical Examination of Learning Orientation, Sales Performance, and Job Satisfaction. *Journal of Personal Selling & Sales Management, 23*(3), 239-251. doi:10.1080/08853134.2003.10749001

Patterson, L. (2007). Marketing and sales alignment for improved effectiveness. *Journal of Digital Asset Management, 3*(4), 185-189. doi:10.1057/palgrave.dam.3650089

Perry, M. L., Pearce, C. L., & Sims Jr, H. P. (1999). Empowered selling teams: How shared leadership can contribute to selling team outcomes. *Journal of Personal Selling & Sales Management, 19*(3), 35–51.

Plouffe, C. R., Williams, B. C., & Leigh, T. W. (2004). Who's on First? Stakeholder Differences in Customer Relationship Management and the Elusive Notion of "Shared Understanding".

Journal of Personal Selling & Sales Management, 24(4), 323-338. doi:10.1080/08853134.2004.10749041

Rajagopal, & Rajagopal, A. (2008). Team performance and control process in sales organizations. *Team Performance Management, 14*, 70-85. doi:10.1108/13527590810860212

Rajagopal, A. (2008). Team performance and control process in sales organizations. *Team Performance Management: An International Journal*.

Rangarajan, D., Jones, E., & Chin, W. (2005). Impact of sales force automation on technology-related stress, effort, and technology usage among salespeople. *Industrial Marketing Management, 34*(4), 345-354. doi:10.1016/j.indmarman.2004.09.015

Rapp, A., Ahearne, M., Mathieu, J., & Rapp, T. (2010). Managing sales teams in a virtual environment. *International Journal of Research in Marketing, 27*(3), 213-224. doi:10.1016/j.ijresmar.2010.02.003

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*, 279-293.

Rapp, A., Beitelspacher, L. S., Schillewaert, N., & Baker, T. L. (2012). The differing effects of technology on inside vs. outside sales forces to facilitate enhanced customer orientation and interfunctional coordination. *Journal of Business Research, 65*, 929-936. doi:10.1016/j.jbusres.2011.05.005

Rapp, A. A. (1989). Team Selling Is Changing The Sales Trainer's Role. *Training; Minneapolis, 26*(5), S6.

Rapp, T. L., Bachrach, D. G., Rapp, A. A., & Mullins, R. (2014). The role of team goal monitoring in the curvilinear relationship between team efficacy and team performance. *Journal of Applied Psychology, 99*(5), 976-987. doi:10.1037/a0036978

Reimann, M., Schilke, O., & Thomas, J. S. (2009). Customer relationship management and firm performance: The mediating role of business strategy. *Journal of the Academy of Marketing Science, 38*(3), 326-346. doi:10.1007/s11747-009-0164-y

Rodriguez, M., & Honeycutt, E. D. (2011). Customer Relationship Management (CRM)'s Impact on B to B Sales Professionals' Collaboration and Sales Performance. *Journal of Business-to-Business Marketing, 18*, 335-356. doi:10.1080/1051712X.2011.574252

Salas, E., L. Dickinson, T., A. Converse, S., & I. Tannenbaum, S. (1992). Toward an understanding of team performance and training. *Teams: their training and performance*.

Salesforce. (2015). Second Annual State of Sales: Insights and trends from over 3,100 global sales trailblazers. Retrieved from https://a.sfdcstatic.com/content/dam/www/ocms/assets/pdf/misc/state-of-sales-report-salesforce.pdf

Silge, J., & Robinson, D. (2017). *Text Mining with R*: O'Reilly Media.

Slater, S. F., & Olson, E. M. (2001). Marketing's contribution to the implementation of business strategy: an empirical analysis. *Strategic Management Journal, 22*(11), 1055-1067. doi:10.1002/smj.198

Smith, A. E. (2003). *Automatic extraction of semantic networks from text using Leximancer.* Paper presented at the Companion Volume of the Proceedings of HLT-NAACL 2003-Demonstrations.

Smith, A. E., & Humphreys, M. S. (2006). Evaluation of unsupervised semantic mapping of natural language with Leximancer concept mapping. *Behavior Research Methods, 38*(2), 262-279. doi:10.3758/BF03192778

Smith, J. B., & Barclay, D. W. (1993). Team Selling Effectiveness:: A Small Group Perspective. *Journal of Business-to-Business Marketing, 1*(2), 3-32. doi:10.1300/J033v01n02_02

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*, 564-579.

Steiner, I. (1978). Task Performing Groups In J. Thibout J. Spence And R. Carson (Ed.) Contemporary Topics In Social Psychology. In: General Learning Press, NJ.

Sujan, H., Weitz, B. A., & Kumar, N. (1994). LEARNING ORIENTATION, WORKING SMART, AND EFFECTIVE SELLING. *Journal of marketing, 58*, 39-52. doi:10.2307/1252309

Tanner, J. F., Ahearne, M., Leigh, T. W., Mason, C. H., & Moncrief, W. C. (2005). CRM in Sales-Intensive Organizations: A Review and Future Directions. *Journal of Personal Selling & Sales Management, 25*(2), 169-180. doi:10.1080/08853134.2005.10749057

Thompson, J. D. a. (2003). *Organizations in action : social science bases of administrative theory*: New Brunswick, NJ : Transaction Publishers, 2003.

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*, 407-428. doi:http://dx.doi.org/10.1007/s11747-010-0211-8

Vilagut, G. (2014). Test-Retest Reliability. In A. C. Michalos (Ed.), *Encyclopedia of Quality of Life and Well-Being Research* (pp. 6622-6625). Dordrecht: Springer Netherlands.

Virtanen, T., Parvinen, P., & Rollins, M. (2015). Complexity of sales situation and sales lead performance: An empirical study in business-to-business company. *Industrial Marketing Management, 45*, 49-58. doi:10.1016/j.indmarman.2015.02.024

Weinstein, L., & Mullins, R. (2012). Technology Usage and Sales Teams: A Multilevel Analysis of the Antecedents of Usage. *Journal of Personal Selling & Sales Management, 32*(2), 245-259. doi:10.2753/PSS0885-3134320205

Wood, R. E. (1986). Task complexity: Definition of the construct. *Organizational behavior and human decision processes, 37*(1), 60-82. doi:10.1016/0749-5978(86)90044-0

Yan, J., Gong, M., Sun, C., Huang, J., & Chu, S. M. (2015). *Sales pipeline win propensity prediction: a regression approach.* Paper presented at the 2015 IFIP/IEEE International Symposium on Integrated Network Management (IM).

Yetton, P. W., & Bottger, P. C. (1982). Individual versus group problem solving: An empirical test of a best-member strategy. *Organizational Behavior and Human Performance, 29*(3), 307-321. doi:10.1016/0030-5073(82)90248-3

Yilmaz, C., & Hunt, S. D. (2001). Salesperson cooperation: The influence of relational, task, organizational, and personal factors. *Journal of the Academy of Marketing Science, 29*(4), 335-357.

Zablah, A. R., Bellenger, D. N., & Johnston, W. J. (2004). Customer Relationship Management Implementation Gaps. *Journal of Personal Selling & Sales Management, 24*(4), 279-295. doi:10.1080/08853134.2004.10749038

Zallocco, R., Bolman Pullins, E., & Mallin, M. L. (2009). A re-examination of B2B sales performance. *Journal of Business & Industrial Marketing, 24*(8), 598-610. doi:10.1108/08858620910999466

Zikmund, W. G., Carr, J. C., Babin, B., & Griffin, M. (2013). *Business research methods*. Nelson: Nelson Education.

Chapter 6: Lead to Win: Machine Learning Recipes for Inside Sales Lead Conversion

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Article Abstract: In inside sales, management of the sales pipeline has traditionally relied on salespeople's intuition and experience-driven predictions. However, this traditional approach has been widely acknowledged as ineffective for qualifying and converting leads to sales (i.e., Wins). Hence, scholars have turned to objective data-driven approaches to guide the sales practitioner's decision-making process as leads advance through the sales pipeline. Notwithstanding, the literature is scarce of lead conversion models that use comprehensive datasets that capture key aspects of the lead engagement process; and models that can provide practitioners with explainable insights on the best lead engagement practices because existing models are based on Black box machine learning approaches. Accordingly, using over 37 million interactions with 7.5 million leads, this study developed several lead conversion models using Machine Learning methods that provide interpretable, explainable, and comprehensible outcomes for both the lead qualification and lead/opportunity management stages of the sales pipeline. The findings of this study provide scholars and practitioners with important lead engagement predictors and insights on the relevance of theses predictors across the stages of the sales pipeline in both B2B and B2C settings.

Keywords: Lead Engagement; Lead Conversion; Machine Learning; Sales Pipeline

Note: This Chapter is an exact copy submitted to the journal referred to above.

6.1.Introduction

Over the last decade, the sales function has experienced a significant reform, mostly powered by digital transformation, technological advances, and social changes (Eitle & Buxmann, 2019; Paschen *et al.*, 2020; Syam & Sharma, 2018). A major driver of this transformation is a growth in size and in importance of the inside sales function, particularly in the context of Business-to-Business (B2B) selling (Rutherford *et al.*, 2014). Inside sales is a selling practice where salespeople engage with prospects, leads and customers remotely using one or more telecommunications technologies (Kawas *et al.*, 2013). The inside sales function becomes a primary contact point for customer acquisition activities, a gatherer of competitive intelligence, and a provider of minor technical and problem-solving assistance to prospects and customers (Harmon & Funk, 2014; Lawrence & Hubbard, 2008).

Management of the sales pipeline (i.e., a progressive process from initial contact with a prospect to the final sales deal) (see Figure 6.1) is crucial for sales organizations in other to improve lead conversion, increase market size, exploit new customer markets, and improve sales success (Bradford *et al.*, 2016; Eitle & Buxmann, 2019). Yet, conversion of prospects to qualified leads and to customers still represents a key challenge for inside sales practitioners (Ohiomah *et al.*, 2019; Sabnis *et al.*, 2013; Smith *et al.*, 2006). Managing leads across the sales pipeline has been mostly guided by personal judgement, professional competence, and prior experience with leads (Bohanec *et al.*, 2017; D'Haen & Van den Poel, 2013) . Such practices introduce personal bias and misjudgments in the process (D'Haen *et al.*, 2016; Eitle & Buxmann, 2019). As a result, most often salespeople redirect company resources to the wrong leads (D'Haen *et al.*, 2016), which could result in less sales opportunities, a decrease in sales productivity and organizational revenue, and an increase in customer acquisition cost (D'Haen & Van den Poel, 2013; Smith *et al.*, 2006).

Subjective decision-making and intuition-based predictions by salespeople are not effective for sales success (Xu *et al.*, 2017). Hence, sales practitioners and scholars are looking into data-driven practices to help manage the sales pipeline. Particularly, a data-driven approach using machine learning (ML) has a potential to fundamentally improve lead conversion and sales performance, and reduce the use of arbitrary rules by inside salespeople while managing leads across the sales pipeline (Eitle & Buxmann, 2019; Magee *et al.*, 2016). Recently, few studies have incorporated ML approaches to improve various stages of the sales pipeline (e.g., Bohanec *et al.*, 2017; D'Haen

& Van den Poel, 2013; Megahed *et al.*, 2016). However, the literature is still characterized by a narrow view and a scarcity of related studies. Particularly, we found that two limitations prevail in the present literature.

Limitation 1: Absence of models using appropriate data that capture key aspects of the lead engagement process.

The most significant body of work on sales pipeline management suggests models to qualify prospects based on predefined features and use historical data about existing customers to classify prospects (e.g., Bohanec *et al.*, 2017; D'Haen & Van den Poel, 2013). Contemporary literature lacks studies that develop models for sales pipeline management using datasets encompassing key aspects of the lead engagement process. Lead engagement factors such as time of call, call frequency, and time to lead (i.e., time from lead identification to contact with the lead) are consistent and applicable to the majority (and probably all) inside sales organizations when salespeople execute their routine sales task. Yet, there is a dearth of academic research offering insights on how such lead engagement factors may help improve lead conversion outcomes across the sales pipeline. This represents a unique opportunity for research. We suppose that prioritizing which lead to pursue, who should pursue the lead and how or when to engage with this lead form a three-way relationship with little to no trade-off between all sides.

Limitation 2: Black box ML approaches do not provide practitioners with comprehensible insights that can assist with decision-making.

Although "Black box" ML usually allows for building top performing predictive models, sales practitioners do not find such models comprehensible. Sales practitioners require relevant and generic insights on practices that can improve the management of the sales pipeline. Black box (i.e., too complex for any human to comprehend) approaches to ML have been widely adopted while investigating sales pipeline management (see Table 6.1). Black box approaches make it difficult (and sometimes impossible) to provide an interpretation of the findings and implications of a suggested model in order to understand how its output was achieved by a given input (Bohanec *et al.*, 2016). Recent studies have proposed ways to explain and interpret the findings of Black box ML models (e.g., Bohanec *et al.*, 2017), but their applications in the management of the sales pipeline are limited. The sales literature still lacks a comprehensive study that itemizes generic and specific insights induced from suggested models. That is, the literature does not offer practical recommendations on the dos and don'ts at various stages of the sales pipeline for specific industries, business situations and customers.

To further highlight the significance of the abovementioned limitations, Syam and Sharma (2018, p. 141), in a review paper, made a call for research on "*how machine learning and AI [can] help develop systems that recommend customer engagement strategies based on analysis of past engagements and their success/failure and depending on salesperson, industry and customer characteristics*". This call for research serves as a key motivation for our study as we aim to answer it with the objective *to develop lead conversion models that can recommend comprehensible, generic, and specific lead engagement strategies for inside sales success*. These models will help to understand the series of sales actions that result in various lead responses and outcomes across specific industries, customers and business contexts.

We achieve the objective of this research, and advance extant knowledge on three main dimensions.

1. We contribute to the sales literature on the ongoing discussion of effective lead engagement. We demonstrate the potential of data-driven analytics by collecting multiple historical datasets from several companies representing different industries for investigation and discovery of insights that will improve lead conversion outcomes.
2. From a methodical perspective, we contribute to the application of explainable ML methods in sales pipeline management.
3. Finally, we provide practitioners with lead conversion models that integrate industry specific performance of salespeople, characteristics of leads and/or prospects and lead engagement strategy aspects, which will help them better understand problems and opportunities in lead engagement, take proactive actions, and improve their sales outcomes.

The remainder of this manuscript progresses as follows. First, we present a brief discussion of the sales pipeline management process and a short review of the extant literature on ML applications in sales pipeline management (see Section 2). Second, we describe the data collection and method of analysis (see Section 3). Third, we detail our analytical results in response to our research questions (see Section 4). Fourth, we discuss the implications of our findings for both theory and practice. Finally, we discuss the limitations of this research and suggest areas for further investigation (see Section 5).

6.2. Sales Pipeline Management

The sales pipeline approach (see Figure 6.1) is used to manage the flow of leads through various stages of the customer acquisition process (Ang & Buttle, 2006; Patterson, 2007). D'Haen and Van den Poel (2013) suggested that customers mature through the sales funnel from *suspects* to *prospects*, to *qualified leads* and finally to *customers* and repeat customers. *Suspects* include a large list of every potential customer in the target market, who are currently not existing customers (Buttle, 2009; Rygielski *et al.*, 2002). *Prospects* include a filtered list of potential customers who meet certain predefined characteristics (D'Haen & Van den Poel, 2013). Lead qualification aims to identify and rank prospects with the highest likelihood of making a purchase (Long *et al.*, 2007). Hence *leads* are qualified (i.e., most likely to respond) prospects that will be contacted by a salesperson to assess their budget, authority, timeline, and product or service need requirements (D'Haen & Van den Poel, 2013; Monat, 2011). Finally, *customers* are leads who end up making a purchase and become clients of the company (D'Haen & Van den Poel, 2013).

Figure 6.1 appears here

A scrutiny of the literature reveals that, from a process perspective, the sales pipeline follows a sales funnel structure that includes stages of *lead generation*, *lead qualification, lead or opportunity management* and *account management* for existing customers (Jaramillo & Marshall, 2004; Smith *et al.*, 2006; Xu *et al.*, 2017). The selling process starts with *lead generation*, which includes all marketing-related activities of identifying leads from a pool of suspects through website visits, filling out online forms, trade shows, etc. (Xu *et al.*, 2017). During *lead qualification*, salespeople evaluate and qualify prospects that first express their interest in a product or service (Kawas *et al.*, 2013). These prospects are qualified to be leads based on their ability to purchase, and their need for the product or service (Xu *et al.*, 2017). Ideally, salespeople spend most of their selling effort qualifying leads (Eitle & Buxmann, 2019).

In the *lead or opportunity management* stage, salespeople constantly nurture and engage with leads via several communication channels (e.g., email, phone, SMS), meeting with the leads to provide product and/or service demos, until a lead converts to a sale (Kawas *et al.*, 2013; Xu *et al.*, 2017). Here, salespeople will assess the product fit with regards to the needs of the lead, identify decision makers in the buying organization, understand budget and timeline considerations, negotiate terms and conditions, and finally convert the lead to final purchase (Xu *et al.*, 2017). The entire sales cycle usually takes, on average, 3 to 9 months, depending on the complexity of the product or service, the industry, and the type of buyer, while some leads take over 1 year to nurture before they can be closed (Syam & Sharma, 2018; Xu *et al.*, 2017). In addition, some leads are removed from the funnel at a certain stage for lack of interest or lack of product fit; some continue to successfully close and convert to sale; while a majority remain in the pipeline until the seller gives up and removes them from the funnel (Bradford *et al.*, 2016).

6.2.1. Application of Machine Learning (ML) in the Sales Pipeline

ML is a branch of Artificial Intelligence (AI) that automates the building of analytical systems that can learn from data, identify patterns, and make predictions based on the data (Mohammed *et al.*, 2016). A scoping review of the literature reveals that the application of machine learning to the sales pipeline has focused mainly on (1) the lead qualification stage; (2) the lead or opportunity management stage; and (3) the end-to-end process from lead qualification to conversion of leads to sales (see Table 6.1 for a summary). Table 6.1 summarizes the findings of the published studies based on the stage of the sales pipeline investigated by the study, the sales outcome measured by the study, the best performing algorithm selected by the study, the visibility of the model in the study (i.e., Black box or Non-Black box) and the contribution of the study to the literature. Arguably, the literature lacks studies on lead generation because lead generation falls within the marketing domain, thus its investigation has eluded the sales management literature. However, overtime scholars have developed ML models to help salespeople advance leads through the sales funnel.

Table 6.1 appears here

To improve lead qualification, studies have suggested various frameworks and models. D'Haen and Van den Poel (2013) proposed a three-stage model to prioritize prospects based on their likelihood of making a purchase. The first stage uses unsupervised ML methods to find similarities between current customers and prospects and accordingly scores and ranks prospects based on their probability to convert to sales. The second stage uses supervised ML methods to estimate the actual probability of winning or losing a sales deal. The third stage uses the outcome of both the supervised and unsupervised ML approaches to provide a ranked list of prospects for sales. Similarly, D'Haen *et al.* (2016) proposed a model for qualifying leads from a list of prospects that are most likely to convert into sales and ultimately into customers. They used information (e.g., industry and company size) located on prospects' websites and, accordingly, employed text mining to qualify prospects as leads who are ready for contact. Furthermore, Gokhale and Joshi (2017) proposed a framework to automate the lead identification and qualification process using a set of automation scripts and ML models. Nygård and Mezei (2020) proposed a lead scoring model using historical transaction data about successful purchases to support salespeople while they pursue leads.

To support the conversion of leads to customers and repeat customers, several forecasting models have been proposed. Yan *et al.* (2015) suggested a model that estimates the win-propensity of sales leads overtime. The model captures and estimates the impact of salesperson activities and lead profile on the Win outcome. To address the limitations coupled with Black box ML models, Bohanec *et al.* (2016) and Bohanec *et al.* (2017) proposed explanation models for predicting the Win and loss of sales opportunities. The proposed models allow users to gain a comprehensive understanding and transparent evaluation of the influence of predictor variables on the outcome. Also, Mortensen *et al.* (2019) also proposed a model to predict Win propensities for individual sales leads and opportunities.

Furthermore, other scholars have suggested models that integrate every process and stage in the sales pipeline. For instance, Megahed *et al.* (2016) proposed a sales pipeline maturity model for forecasting sales generated by opportunities while minimizing the average error rates by factoring conversion rates and growth factors in historical sales data. The model can also identify the number of historical periods needed for sales prediction. Xu *et al.* (2017) proposed a data-driven system for client specific forecast that could be applicable across several sales patterns, products and sales teams. Additionally, Eitle and Buxmann (2019) proposed a model to help salespeople in the software industry manage leads across the three stages (i.e., initial lead phase, opportunity phase, and sales deal closing) of the sales pipeline. They also used an explanation model to facilitate the understanding of the impacts of different features.

Despite the effort of Bohanec et al. (2016), Bohanec *et al.* (2017) and Eitle and Buxmann (2019) to mitigate the limitations inherent to Black box models, such studies do not offer the insights desperately needed by practitioners in the management of the sales pipeline. Moreover, such studies are somewhat limited by the size of their datasets and the features they leveraged. To summarize, ML approaches to sales lead conversion have been a tale of approaches. On the one hand, scholars have used *interpretable ML methods* such as decision trees and logistic regression that provide useful model outputs such as variable monotonicity, causality between variables, and constraints that are domain-specific (Huysmans *et al.*, 2011; Rudin, 2019). On the other hand, scholars have used *explainable Black box ML methods* that show the relationships and impact of predictor variable inputs on outcome variable outputs of Black box *methods* (e.g., random forest, neural networks, support vector machines e.t.c) in a way that humans can understand (Rudin, 2019). Although, Black box ML methods arguably can provide the best performance compared to interpretable ML methods, particularly on large and complex datasets, explainable Black box ML models are sometimes not reliable and can be misleading (Rudin, 2019). Hence, this study uses both interpretable ML methods that output their explanations and Black box ML methods that use other means to explain their output. We believe that the proposed approach will provide models that offer interpretable, explainable, and comprehensible insights on the best lead engagement practices.

6.3. Research Design

In this research, we implement a data-driven approach using ML methods to develop lead conversion models that can recommend the optimal lead engagement strategies to adopt with sales leads. From an ML perspective, it is quite interesting to study sales lead conversion because sales lead engagement data is highly imbalanced and requires adequate attention in preprocessing and model building. Using ML, this study aims not only to predict lead conversion outcomes but also to explain why salespeople Win or lose sales leads. Indeed, this study goes beyond reporting the performance of implemented predictive models by capturing and interpreting the patterns learned from the data. Next, we discuss the data used for this study and highlight the key variables and terms relevant to the research design.

6.3.1. Data Preparation

We collected nearly 300 million records of data from our industrial partner, a leading Lead Management System (LMS) software provider and a marketing automation company in North America. Data records consist of over 100 data fields including lead characteristics, contact history information, sales information, etc. The data represents the transactions of 551 inside sales companies (companies that use inside sales as opposed to face-to-face sales) with their sales leads from 2005 to 2018 and covers a variety of industries. The data was generated by inside salespeople using the LMS as they made calls to qualify leads, nurture leads, make sales proposals or closing, and up-selling or cross-selling to existing customers.

The data was pre-processed to eliminate irrelevant variables, outliers, missing values, and a high number of classes in some categorical variables. Additionally, we generated new variables using computations involving existing variables. The data transformation process generated a reduced but higher-quality dataset that may help lessen the complexity of our data analysis and improve the generalization of our findings (Yu *et al.*, 2006). The R Studio tool (version 3.6.2) was used to clean, prepare, analyze, and visualize the data. Table 6.2 describes the variables included in this study. There are 16 variables that conceptualize salesperson effort (i.e., average number of calls and contact attempt), salesperson performance (i.e., ratio of won leads), salesperson experience, days to lead and call duration, call time, call day, company business model, industry, lead location and sales pipeline stage .

Table 6.2 appears here

Next, we selected the Interaction Outcome variable from the dataset to account for the outcome of the interaction with a lead. Originally, the data included over 5,000 different call outcomes because of the diversity of companies and individual projects. Most of the outcomes were the same, however, there were spelling, abbreviation and synonymic differences in their usage. Accordingly, we identified three possible outcomes for an interaction: *Unknown, Loss* and *Win*, which are in line with Yan *et al.* (2015) conceptualization of sales outcomes. An outcome is classified as *Unknown* if a contact with a lead was not attempted yet; the phone line was disconnected or busy; the decision maker was not reached or was unreachable; contact information was wrong or incomplete; another decision maker's contact information was provided; or lead requested a call back. Leads with this outcome might still be undergoing some form of prospecting qualification, follow-up calls are still being made, and emails or voicemails are being left for the lead by the salesperson. An outcome is recorded as *Loss* if a salesperson failed to qualify or convert a lead at any point in the sales process. Finally, a *Win* (i.e., Success) outcome includes qualified sales leads that have shown interest and or requested or booked appointments and demos, etc. Win also includes instances were a sales goal was successfully achieved, for instance, a product or service was sold.

Furthermore**,** we subset the data to include only those relevant instances where a lead interaction ended in a Win or Loss outcome and exclude those that end with an Unknown outcome. This will allow us to find the optimal lead engagement strategies to adopt with leads and investigate the combinations of touches (i.e., contacts) that could yield a Win outcome at the end of the sales pipeline. Accordingly, we prioritize leads that were either Win or Loss at the end of the sales pipeline only, because as a lead moves through the different stages of the sales pipeline, it can have Win, Loss and Unknown outcomes. For instance, a salesperson called a lead for the first time (Touch 1) and did not reach it but left a voicemail (outcome: unknown). A day later, the salesperson called the lead again and was able to connect with the lead and request an appointment for a product demo to which the lead said yes (outcome: win). However, after the demo (Touch 3), the lead declined to buy the product/service (outcome: loss). As can be seen in this scenario, the first outcome (unknown), was not the same as the last one (loss) for several reasons (e.g., lack of sufficient budget, lack of product/service fit, etc.). If the last outcome is Unknown, we excluded such interactions since they are not within the scope of our study. In order to select the appropriate data needed for our study, we implemented the following procedures:

- First, we mapped out the last interaction instance with every lead within our dataset.
- Second, we removed leads which last interaction outcome were unknown and contacted within 365 days of the date we collected the data. Hence, we cleaned out the data of leads that have not yet completed their sales cycle. This procedure is in line with the literature suggestion that the sales cycle of some leads may last up to one year (Syam & Sharma, 2018; Xu *et al.*, 2017).
- Third, we selected leads that ended in a Win or loss outcome leaving out those contacts whose last outcome was unknown.
- Last, we matched all the leads with a final Win or loss outcome to the original data. Therefore, we constructed a dataset focused on leads that either ended in a Win or loss but could have had unknown outcome instances as they moved through the sales pipeline.

To conclude the data preparation process, we identified the stages of the lead in the sales pipeline by implementing a text mining procedure to group data instances based on outcomes recorded by salespeople for each interaction with a lead. We implement Latent Dirichlet Allocation (LDA) model on the textual data (data entered by salespeople to document their interactions with leads). LDA is a generative probabilistic model that can be used to classify and summarize text documents based on co-occurrence and semantic connection words (Blei *et al.*, 2003; Silge & Robinson, 2017). LDA assumes that documents are combinations of topics, and each topic is a combination of words (Blei *et al.*, 2003). To estimate the probability of a corpus, LDA computes and assigns probability to members of the corpus, as well as other similar documents. The function is given as:

$$p\ (\mathrm{D}|\alpha, \beta) = \prod_{d=1}^{M} \int p(\theta_d|\alpha) \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(\mathrm{z}_{dn}|\theta_d) p(\mathrm{w}_{dn}|\mathrm{z}_{dn}, \beta) \right) d\theta_d$$

Where α and β are corpus (i.e., collection of documents) parameters sampled once; θ_d are document (i.e., sequence of N words) variables, sampled once per document; and z_{dn} and w_{dn} are words (i.e., basic units of discrete data) variables sampled once for each word in each document (Blei *et al.*, 2003).

6.3.2. Machine Learning (ML) Methods

ML makes available several standard algorithms – i.e., *"iterative step by step process[es] to transform inputs to output"* (Kotu & Deshpande, 2014, p. 4) - that are ready to be deployed for building models that can solve complex problems. In this study, developing lead conversion models uses several independent variables to predict and classify the outcome (i.e., win, loss and unknown) of an interaction with a lead across stages of the sales pipeline. By definition, this is a supervised ML problem (i.e., training a model using labeled instances, and then using the trained model to map and classify new instances).

In this study, we implement ML algorithms based on their different learning processes and techniques: Decision-based classifier using *Classification and Regression Tree (CART)*, Ensemble-based classifier using *Random Forest (RF)*, Regression based classifier using *Logistic Regression (LR)*, and a Probabilistic-based classifier using *Naive Bayes (NB)*. The decision to use these algorithms stems from their applicability to this research problem and data, as suggested by the literature, as well as their ability to interpret or explain their findings. These algorithms are discussed below.

Classification and Regression Trees (CART) Algorithm: The CART Algorithm is a decision tree technique for splitting trees. It searches the dataset and builds the tree by splitting the attributes in the dataset into groups and subgroups based on the similarity of the observed values of each attribute (Crawford, 1989). Dissimilar datasets are then partitioned into sub-groups, with each sub-group containing similar observations (Crawford, 1989). We use the Gini index (see Raileanu and Stoffel (2004) for a description) to evaluate the partitioning of the data before splitting it in CART. We selected the CART algorithm because it provides explanations about prediction outcomes (i.e., variable importance, decision tree and decision rules). CART is also non-parametric, making no assumptions about distribution for input or outcome variables (Abbott, 2014; Łapczyński & Jefmański, 2014; Lee & Wu, 2012; Quinlan, 1986).

Random Forest (RF) Algorithm: RF belongs to a class of algorithms called ensemble learners. This learning technique combines multiple classifiers with different performance levels into one ensemble classifier, with a primary goal of getting accurate and consistent predictions that outperform any individual classifiers (Breiman, 2001). The RF algorithm computes different bootstrap samplings of the data and constructs multiple decision trees in such a way that each tree is grown by randomly selecting the best among all predictor variables and randomly selecting a subset of data cases while splitting a node (Breiman, 2001). RF grows trees to maximum size without pruning, thereby reducing variance and inducing diversity among trees (Murphy, 2012).

The outcome of an RF algorithm is an ensemble classifier that summarizes the classification performance of all the developed trees combined (Breiman, 2002). For classification performance, RF utilizes a majority vote to choose the class label for unlabeled observations. We selected the RF algorithm because it has very good classification accuracy and has been applied in many fields (Murphy, 2012). Plus, multiple decision trees can be trained in parallel thus limiting generalization error, and lowering the risk of overfitting and bias (Murphy, 2012). Additionally, the outcome of RF models can be implemented using explainable ML methods.

Logistic Regression (LR) Algorithm: LR is a broadly used ML and statistical approach that models the relationship between several predictor variables and an outcome discreet variable without much restrictions (Kotu & Deshpande, 2014; Murphy, 2012). LR investigates the probability of an event occurring based on the values of the predictor variables, which can be continuous or categorical (Bewick *et al.*, 2005). Moreover, LR uses a non-linear transformation function of the outcome called a logit function or sigmoid function to successfully map the ratio of the outcome probabilities (Murphy, 2012). The goal of logit is to place the value of the predictor variable between a probability of 0 (i.e., "non-event") and 1 (i.e., event) of the outcome variables.

LR uses MLE (Maximum Likelihood Estimation) to compute the coefficient of the predictor variable and explain the relationship to the outcome variable (Murphy, 2012). The coefficient can be interpreted as odds ratio, a degree of relative risk associated with a specific covariate pattern (Murphy, 2012). We selected LR in this study as the model can effectively explain the variation in values of the outcome variable and estimate the significance of each independent variable to determine if the independent variable adds to the strength of the model or not.

Naive Bayes (NB) Algorithm: NB is a probabilistic classifier that computes a set of probabilities by tallying the frequency and combinations of values in the dataset (McCallum et al. 1998). The algorithm applies the Bayes' theorem and assumes the effect of the value of a predictor variable on a given class is unrelated and independent of the values of other predictors, even if these predictor variables depend on each other or upon the existence of other predictor variables (Murphy, 2012). The existence of a feature in a class is unrelated to any other feature's existence. The probability of each class and the conditional probability for each class given each predictor value are calculated from the training data to map new instances (Mohammed *et al.*, 2016). We selected NB because it is fast, easy to implement and suitable for large datasets like the one used in this study (Abbott, 2014). Additionally, the outcome of NB models can be implemented using explainable ML methods.

6.3.3. Explainable Machine Learning (ML): The EXPLAIN method

Understanding the patterns learned from the implementation of some ML algorithms like DT and LR is not challenging since their model outputs are self-explanatory. However, interpreting the outputs of Black box algorithms can be a challenge. Hence, we implement the EXPLAIN method (Robnik-Šikonja & Kononenko, 2008) for the explanation of patterns learned from the implemented algorithms such as RF and NB. The EXPLAIN method uses a sensitivity form of analysis to extract model explanations by observing the positive or negative contributions of individual predictor attributes to a given outcome class by hiding the input predictors and observing how the outcome class changes (Štrumbelj & Kononenko, 2014). EXPLAIN captures the causal relationship between predictor and outcome variables and can produce simple, comprehensible and graphical visualizations of models (Robnik-Šikonja & Kononenko, 2008).

Using the one-variable-at-a-time approach, the EXPLAIN method computes the contribution of a variable *i* when predicting an instance *x* as the difference between the model's prediction for that instance *x,* as well as the model's prediction if the value of variable i is unknown. A small difference means the variable i is less important, while a large difference means variable i is important. Additionally, a value greater than 0 means that variable *i* contributes positively towards the outcome class value y_k, while a value less than 0 means that variable *i* contributes negatively towards the outcome class value y_k. As suggested by Bohanec *et al.* (2016), we use the log-odds ratio approach to improve the understanding of the model's outcome. The function is given as:

$$WE_i(k,x) = \log_2\left(\frac{p(y_k|x)}{1-p(y_k|x)}\right) - = \log_2\left(\frac{P_{S\{i\}}(y_k|x)}{1-P_{S\{i\}}(y_k|x)}\right)$$

Were $p(y_k|x)$ is the expected prediction for class value y_k, and $P_{S\{i\}}(y_k|x)$ is the expected conditional prediction (i.e., the prediction for which only a subset of the input variables is known). The EXPLAIN method's outcome includes a visual model explanation of an average of instance explanations on the training instances and provides an impact of predictor attributes to the outcome class and their values in the model (Bohanec *et al.*, 2016; Bohanec *et al.*, 2017).

6.3.4. Model Evaluation and Imbalanced Dataset Problem

This study implements a 10-fold cross-validation to evaluate and compare the performance of the selected algorithms. 10-fold cross-validation has been suggested in the literature as an effective choice for model evaluation (Kohavi, 1995). In addition to using 10-fold cross-validation, this study uses common measures (i.e., Classification accuracy, Sensitivity (or Recall) and Specificity) to evaluate model performance. Since our dataset suffers from large class imbalance, there is a possibility that some of the models can effectively classify instances of the majority class and thus will attain misleading high classification accuracy or suffer a trade-off between sensitivity and specificity (Akosa, 2017; Kubat *et al.*, 1997; Napierala & Stefanowski, 2012). Therefore, this study also uses balanced accuracy, geometric mean and F-measure to compare model performance (Akosa, 2017).

Furthermore, the dataset collected by this study is imbalanced (i.e., unequal distribution of instances in each outcome variable). On average, only 5% of all instances have a Win outcome, about 10% of the instances have a Loss outcome, and the remainder is categorized as Unknown. The small number of data instances present in the minority classes makes it difficult for ML algorithms to perform classification effectively. Imbalances in data can cause higher misclassification rates of the minority class during the algorithm evaluation stage as the calculation of accuracy is more drawn to the majority class and not so much to the minority class (He & Garcia, 2009; Weiss, 2004). Additionally, it may become difficult to distinguish between a minority class and noisy data. Finally, it may make it difficult for CART algorithm to find appropriate learning rules for the minority class because top-down induction uses maximum generality bias based on instances in the training data to learn and infer rules (Jo & Japkowicz, 2004; Napierala & Stefanowski, 2012; Weiss, 2004).

Form our data perspective, Win and Loss instances are rare and likely to have more distinct features compared to Unknown instances. However, Unknown instances are comparatively more prevalent and likely to have fewer distinct features that separate them from Win and Loss instances. Moreover, the data sub-setting approach we suggested in Section 3.2 may change the data distribution in favor of the Win and Loss instances, giving the majority of data samples. To address this data imbalance issue, we resample the data by:

- Over-sampling – randomly adding instances to the minority class.
- Under-sampling – randomly removing instances from the majority class in order to yield a completely balanced dataset (Jo & Japkowicz, 2004).
- Synthetic Minority Oversampling Technique (SMOTE) **-** using the k-nearest neighbor technique to generate random synthetic instances for the minority class, while concurrently removing samples from the majority class until the minority and majority classes share a similar proportion of data samples (Chawla, 2005). SMOTE approach helps generate an alternative balanced dataset for the selected algorithms because the literature suggests that oversampling may lead to model overfitting and under-sampling may possibly remove instances that may be crucial for the classification goal (Chawla, 2005; Napierala & Stefanowski, 2012).

6.4. Results

The final data sample after pre-processing included data from 55 companies representing 4 service-based industries namely Financial services, Insurance, IT Services, and Marketing and Advertising. We focus on these four service industries because insights generated from these industries may be applicable to the service industry at large. We started with about 100 million records for the 55 companies. After applying the procedure discussed in section 3.1, we ended up with a sample of 37,859,241 interactions with 7,503,342 leads. We treat each interaction with a lead as an instance in the dataset. Table 6.3 shows the summary of our dataset.

Table 6.3 appears here

6.4.1. Stages of the Sales Pipeline Using Text Mining

We classified interactions into four stages of the sales pipeline by implementing a text mining procedure on 9216 unique results (i.e., text documenting the outcome of an interaction with a lead). The high number of unique results is due to the high number of projects (i.e., 10272 projects for the 55 companies selected for the study). Each project (i.e., a sales project) included datasets for different leads and had different sets of interaction outcomes. Examples of these projects include lead qualification and lead/opportunity management.

We implemented LDA modelling (using R Version 3.6.2) and processed the data by removing punctuation, numbers, stop words and whitespaces from the text. To identify the number of topics to use as input for the LDA model, we used perplexity (i.e., a statistical measure of how well a probability model predicts a sample). Perplexity identified 105 topics (see Figure 6.2) which were fed to the LDA model.

Figure 6.2 appears here

Consistent with scholarly practices (Chuang *et al.*, 2015; Jacobi *et al.*, 2016), we manually coded each identified topic into one of the four categories, namely *No Contact*, *Lead Generation*, *Lead Qualification* and *Lead/Opportunity Management*. The identified categories were validated with prior literature, as well as through industry expert panels. We successfully classified 7,637 (82.9%) of the unique results using the identified 105 topics into these four categories. We deleted the interactions with results that could not be classified. The boundaries of these 4 categories are discussed below.

- **No Contact:** This category includes instances where a salesperson made an interaction attempt but was unable to reach the lead because the number of the lead was busy, invalid, duplicated, disconnected, etc.
- **Lead Generation:** This category includes instances that resulted in the validation or no validation of a potential lead that may or may not be pushed further to the qualification stage. Outcomes here include information update, no information, deceased, verified lead, future lead, referral etc.
- **Lead Qualification:** This category includes instances that resulted in a meaningful contact with a lead and a decision of interest or no interest expressed by the lead or the salesperson. Such interactions include instances where the lead confirms interest in the product or service, makes registrations, completes surveys, or the lead expresses lack interest by refusing an appointment, hanging up, requesting to be on a "Do Not Call" list, etc. Also, it includes outcomes when the salesperson qualifies of disqualifies the lead for having met or not met specific criteria for the product or service, could not identify the decision-maker, language barrier, further information is needed on the lead, etc.
- **Lead/Opportunity Management:** This category includes instances that resulted in lead or opportunity nurturing outcomes and conversion to sale outcomes. Favorable outcomes include appointment/demo scheduled, demo/appointment requested, info/proposal/quote sent or requested, partially completed deal, met with "someone", accepted an offer, closed deal, sold and won etc. Unfavorable outcomes include cancellation of appointment/process, withdrawal, declined offer, request for a refund, lost to a competitor, etc.

As mentioned earlier in this paper, we removed instances where the outcome was "No contact" because it is beyond the scope of this study, and we do not seek to generate insights about lead engagement practices where no interaction occurred. *Lead Generation*, *Lead Qualification,* and *Lead/Opportunity Management* represent actual stages a lead goes through during its journey in the sales pipeline (see Figure 6.1). Additionally, we identified that lead generation only had 0.2% of the data distribution (see Table 6.3). The small proportion is because lead generation is mainly a marketing task, and only occurs within sales during the lead qualification process through referrals and lead verification procedures. Hence, we combined the data for lead generation and lead qualification together as lead qualification. Ultimately, we ended up with two stages for our investigation (i.e., *lead qualification* and *lead/opportunity management*). Table 6.3 shows the distribution of data between the stages of the pipeline.

6.4.2. Modelling Procedure

We developed several lead conversion models using 4 different classifiers: DT, LR, NB, and RF. We divided our dataset by randomly taking 70% of the instances as a training set and the remaining 30% for testing the performance of each model. In addition, we applied random under sampling, random oversampling and SMOTE sampling techniques on the training set for each classifier to address the issue of class imbalance. We further partitioned our data based on the type of sale (i.e., B2B– Business-to-Business or B2C – Business-to-Consumer). This means that we implemented 4 models for each of the selected methods (i.e., 4 x 4 = 16), for both B2B and B2C business models (i.e., 16 x 2 = 32), for both the lead qualification and lead/opportunity management stages (i.e., 32 x 2 = 64). Ultimately, we implemented a total of 64 models.

Each model is built using 10-fold cross-validation and repeated ten times to increase the stability and reliability of model performance. The performance of all classifiers is evaluated by the measures discussed in Section 3. Moreover, we only focus our discussion on aggregate performance metrics such as F-measure, G-mean and Balanced accuracy (see Section 3.4 for descriptions) that effectively capture model performance on both the minority and majority class.

6.4.3. Model Results

We structure the discussion of the results based on the lead qualification and lead/opportunity management stages. We first discuss the performance of the implemented algorithms. Then, we interpret and explain the findings of each of implemented algorithm for both B2B and B2C. By default, the CART and LR models provide interpretations and explanations on patterns, dependencies and relationships in the model. The RF and NB models are considered Black box models and by default offer no simple way to explain their predictions. Hence, we use the ExplainPrediction algorithm to explain the findings of both the RF and NB models. Note that for each algorithm we only explain and interpret the models with the best performance.

The ExplainPrediction models for RF and NB are shown in Figures 6.3 to 6.10. The impacts of the predictor variables and predictor's values (i.e., indicators) on the outcome variable are expressed by the length of the horizontal bars. Each predictor variable (the weighted averages of the impact of the associated predictor values) are represented by a dark grey horizontal bar, and the associated predictor values by a light grey horizontal bar. Each predictor variable and its values are separated from other predictor variables and their values by a dashed line. The bars on the right side show positive impact on the outcome class value (i.e., Win), and the bars on the left side show a negative impact on the outcome class value. The scales of the horizontal axis are based on the normalized sum of contributions in a range of 0 to 100. The predictor variables are ordered by importance (i.e., higher impact) in the model from top to bottom.

Lead Qualification Stage

Lead Qualification Model Performance: Table 6.4 shows the performance of the four classifiers on each dataset (i.e., baseline, oversampling, under sampling and SMOTE), as well as the number of data instances used to train the classifiers for the lead qualification stage. Overall, the RF classifier had the best performance across all sampled datasets with f-measure, g-mean and balanced accuracy values ranging from 85.2% to 94.6% for B2B, and 64.7% to 92.9% for B2C. The RF oversampled model had the highest performance when we average the f-measure, g-mean and balanced accuracy among all the B2B models (i.e., 92.2%), and B2C models (i.e., 85.4%). Additionally, the NB classifier had the lowest performance with f-measure, g-mean and balanced accuracy values ranging between 50.3% to 79.9% for B2B, and 33.1% to 71.4% for B2C. Furthermore, we found that the under-sampling and oversampling models for both CART, LR and NB produced similar results for both B2B and B2C.

Table 6.4 appears here

***Lead Qualification Model Interpretation and Explanation*:** The CART algorithm produces the importance of predictor variables, a decision tree and corresponding decision rules for the decision tree. Table 6.5 shows the variable importance of the CART SMOTE model for both B2B and B2C. The variable importance score indicates the relative importance of that variable in splitting nodes of the decision tree. Salesperson performance and industry (i.e., Insurance and Financial services) are key splitting predictor variables for B2B, while salesperson performance, industry (i.e., Insurance and Financial services), call duration and salesperson effort are key splitting predictor variables for B2C. The rules induced from the CART models show that high performing salespeople have a high tendency to Win leads, and the chances to Win are greater if the salesperson can maintain medium to long phone conversations (i.e., call duration) with leads during B2B lead qualification. However, the B2C CART model reveals that medium to high performing salespeople have high chances to Win leads, particularly when the salesperson can make a high number of sales calls (i.e., effort), have medium to long phone conversations with leads and send small sized emails.

Table 6.5 appears here

The outcome of the LR model shows the path coefficients and significance of predictor variables in the model. Table 6.6 shows that calling on Sundays, Mondays, and Thursdays were non-significant predictors in the B2B lead qualification model. Calling on Thursdays and Fridays were non-significant predictors in the B2C lead qualification model. Similar to the CART lead qualification model, salesperson performance is a key positive driver of Win outcomes for B2B, while salesperson performance and industry (i.e., Insurance, IT Services and Financial Services) are positive drivers of Win outcomes for B2C during the lead and opportunity management stage.

Table 6.6 appears here

The outcome of the lead qualification RF models for B2B and B2C are shown in Figures 6.3 and 6.4. By order of importance, the B2B model shows that salesperson performance, industry, call duration, and contact attempts are key predictors in the model. However, the B2C model shows that salesperson performance, call duration, industry, average number of calls, and contact attempts are key variables in the model. The predictor values of the B2B model show that high performing salespeople, IT service industry, and long call durations with leads have more positive than negative impacts on Win outcomes. While the B2C model reveals that medium to high performing salespeople, all call durations levels, the insurance industry, and salespeople with one or more years of experience have more positive than negative impacts on Win outcomes during the lead/opportunity management stage.

Figure 6.3 appears here

Figure 6.4 appears here

Lead qualification NB models results (see Figures 6.5 and 6.6) show that salesperson performance, lead type, industry, sales cycle time, contact attempts, and salesperson average number of calls are key predictors in the B2B model. Whereas, salesperson performance, industry, average number of calls, salesperson experience and call duration were the top predictors in the B2C model. Medium to high performing salespeople, financial service industry, six or more contact attempts, and long call durations have more positive impact on Win outcomes for B2B. For B2C, medium to high performing salespeople, Marketing and Advertising, Financial service industry, moderate to long call durations, and salespeople with one or more years of experience have more positive impact on Win outcomes.

Figure 6.5 appears here

Figure 6.6 appears here

Lead/opportunity management Stage

Lead/Opportunity Management Model Performance: At the lead and opportunity management stage, the RF classifier had the best performance across all sampled datasets with f-measure, g-mean and balanced accuracy values ranging from 93.2% to 97.8% for B2B, and 96.8% to 99% for B2C (see Table 6.7). The average of f-measure, g-mean and balanced accuracy for the RF SMOTE and RF under-sampled models are similar and perform the best among all the B2B models (i.e., 95.5%), while the RF oversampled dataset performed the best for the B2C models. Consistent with the findings of the lead qualification stage, the NB classifier had the lowest performance with f-measure, g-mean and balanced accuracy values ranging from 73.8% to 87.6% for B2B, and 78.5% to 86% for B2C.

Table 6.7 appears here

Lead/Opportunity Management Model Interpretation and Explanation: Table 6.8 shows the variable importance of the CART model for both B2B and B2C. Email source, email size, call duration, and salesperson performance are key splitting predictor variables for both B2B and B2C. Particularly, the rules induced from the B2B CART model show that medium to high performing salespeople have high tendencies to Win leads, particularly when the salesperson can maintain medium to long phone conversations with leads, with small to medium effort levels and send small to medium-sized emails that receive responses. The B2C CART model shows that high performing salespeople have high tendencies to Win leads, particularly when the salesperson can maintain medium to long phone conversations with leads and send small sized emails.

Table 6.8 appears here

Additionally**,** Table 6.9 shows the path coefficients and significance of the LR model. All predictors in the B2B model were statistically significant except calling on Mondays, Thursdays, and email sent. For the B2C model, calling Web leads, email size, average income, calling on Thursdays, and the financial services industry were found not statistically significant. Salesperson performance is a key positive driver of Win outcomes for B2B, while salesperson performance and industry (i.e., Insurance and IT Services) are key positive statistically significant of Win outcomes for B2C during the lead/opportunity management.

Table 6.9 appears here

The outcome of the RF models for B2B and B2C are shown in Figure 6.7 and 6.8. The B2B model ranks industry, salesperson performance, email source, email size and average number of calls as key predictors in the model. Particularly, high performing salespeople, long call durations, calling leads within the first day, and Web leads have more positive than negative impact on Win outcomes for B2B. Industry was the most important predictor for B2B, all industries have a similar variation in positive and negative impact on the Win outcome during the lead/opportunity management stage. The B2C model shows that salesperson performance, email size, call duration, and email source are key variables in the model. Particularly, medium to high performing salespeople, medium to long call durations, calling leads within the first day and salespeople with one or more years of experience have more positive than negative impact on Win outcomes during the lead/opportunity management stage.

Figure 6.7 appears here

Figure 6.8 appears here

Finally, the results of the NB model show that email source, call duration, salesperson performance and email size are key predictors in the B2B model (see Figures 6.9 and 6.10), while salesperson performance, email source, email size, call duration and email sent where the top predictors in the

B2C model. Particularly, high performing salespeople, long call durations, calling leads within the first day and salespeople with one or more years of experience have more positive impact on Win outcomes in both the B2B and B2C model.

Figure 6.9 appears here

Figure 6.10 appears here

6.5. Discussion and Conclusion

Over the years, managing the sales pipeline has been ruled by practices that rely heavily on personal judgement, professional competence, and prior experience, which often limited lead conversion ratios across the sales pipeline. Accordingly, researchers have turned to ML as an alternative approach to build lead conversation models. But despite those research initiatives, the literature still lacks studies that provide insights into the best lead engagement practices using appropriate data. Using over 37 million interactions with 7.5 million leads, we developed several lead conversion models using four ML classifiers (i.e., CART, LR, NB and RF) that provide interpretable and explainable outcomes of patterns identified in the data for both the lead qualification and lead/opportunity management stages of the sales pipeline.

The evaluation of the models suggests that ensemble-based methods (i.e., RF) can improve the predictive performance of a lead engagement dataset, while probabilistic-based methods (i.e., NB) are not the best classifiers for a lead engagement dataset. Next, we highlight notable findings and implications derived from a closer look at the models' outcomes on series of sales actions that led to various lead responses and outcomes for specific situations, industries, leads, and business contexts.

6.5.1. Implications

Hire and Train Salespeople to be Closers

We found that salesperson performance was ranked the most important predictor for the lead qualification and lead/opportunity management stages in both B2B and B2C. Although the notion that the best performing salespeople engage effectively with leads is not surprising or a new contribution to the literature, it further affirms the importance of high performing salespeople. Accordingly, we stress that sales organizations should continue to hire the best salespeople and or coach their salespeople on effective lead engagement practices that can improve lead conversion outcomes. Sales practitioners should also assign priority and Web leads to their best salespeople even during the qualification and management stages of the sales pipeline.

Quality Conversations are Key to Successful Sales Interactions

We found that call duration is important for the lead qualification and lead/opportunity management stages in both B2B and B2C. The longer a salesperson can keep a lead engaged in a conversation, the better the chances of a Win outcome. While conversations are usually shorter during the lead qualification stage, conversations do increase later in the lead/opportunity management stage of the sales pipeline. Hence, we encourage salespeople to continue pushing for conversations even though they may face resilience from leads at the initial stages of the sales cycle. We also encourage sales managers to continue to coach salespeople to construe and hold longer conversations during interactions with leads.

"Act Now" or "Lose out"

Past studies have suggested that leads contacted within the first five days of being identified have a 20% better chance of making a purchase than those contacted later (e.g.,Smith et al., 2006). Similarly, we found that the best practice is to contact B2B and B2C leads within the first three days of inquiry, while specific effort should be made to contact B2B Web leads within the first day of inquiry. Unquestionably, when a lead has self-identified, it means the lead potentially has an interest in the product and/or service offering. At this point, it becomes a matter of who reaches out first to the lead among all salespeople. Hence, salespeople who are not first and subsequent responders will likely lose the lead to a competitor or the lead may lose interest in the product or service offering as time passes.

Additionally, we found that the sales cycle time for Web leads is shorter than non-Web leads. Hence, salespeople need to make an effort to complete the lead qualification process for B2B and B2C Web leads within the first day of contact. This is particularly important for B2C leads which have a shorter sales cycle than B2B leads. The sales cycle for B2B leads is usually longer depending on the product or service being sold. We found that the Win ratio for B2B leads is stable as the sales cycle time increases. Hence salespeople should never stop nurturing B2B leads until they are completely certain that the lead is lost.

Getting the right lead to answer the first call or book the first appointment for a sales demo is often the most crucial part of the inside sales process. Accordingly, we encourage salespeople to respond immediately to all leads after an enquiry is made. Salespeople should follow-up with leads with persistence during the early stages of the lead cycle. For leads that could not be reached during the first attempt, the second contact attempt should be made on the same day. Those with successful outcomes on the first attempt should schedule their second and subsequent attempts at the earliest time possible.

An Email Sent Right Gets the Right Attention

Our analysis shows that email sent was another important variable, particularly during the qualification of B2B leads. During lead qualification, emails should be sent to B2B leads to follow-up on calls. Such emails can include an appreciation of time and effort to talk to the salesperson, and suggested resources about the products and services. Such suggestions can help the leads as they continue to search for information to make their purchase decision. In situations where a lead could not be reached, the best practice for salespeople is to leave voicemails and or send emails. During lead/opportunity management, emails should only be sent to B2B leads as needed to facilitate appointments and meetings for product and service demos. Such emails can be appointment notifications and product or service promotions.

It is important not to blast B2C leads with too many emails during lead qualification, as our analysis shows that sending an email, particularly of medium to large size, could potentially harm Win outcomes with B2C leads during lead qualification. We suggest that follow-up emails be only sent to B2C leads during the lead/opportunity management stage when the leads have already been qualified. These should be medium to large-sized email that can help B2C leads make and finalize their purchase decisions.

A Misdirected Effort is Counterproductive

Call productivity (i.e., the number of sales calls made over a period of time) and lead contact persistency have served as key indicators of salesperson effort in the literature (Cartera et al., 2014; Ohiomah et al., 2019). Our findings reveal that salespeople with a high average number of calls (i.e., 100 calls and above) have lower Win ratios. Such results on the negative impact of salesperson effort are intriguing but are in line with findings by Hunter and Perreault (2007), Cartera et al. (2014) and Ohiomah et al. (2019) who detected a non-significant relationship between the effort of a salesperson and sales success. Salespeople should channel some of their calling effort towards following up on leads they have previously established contact with. Then, an increase in the number of calls would increase contact attempts with a particular lead, which can ultimately improve the chances of a Win outcome. It is a fact that some salespeople make single attempts to several leads in order to meet their dial quotas, hurting their chances of a Win outcome in the process.

Nevertheless, we found that more contact attempts are needed to qualify B2B leads, and the best practice is to make at least six contact attempts before giving up on such leads. B2C leads do not require as many contact attempts as B2B leads during lead qualification. Our analysis suggests between two to five attempts to qualify B2C leads. We found that that most B2C leads with six or more attempts are not likely to end up in a Win outcome during the qualification process. Hence, salespeople should avoid spending more time on B2C leads that go cold after the first five attempts, because chances they could convert them to appointments or sales are rather low.

Experience is a Teacher, the More you Sell the More you Win

Our findings suggest that salespeople with more experience (i.e., amount of time spent working with the current company as a salesperson) are more likely to have Win outcomes with leads than salespeople who are less experienced. The best practice shows that salespeople with one to five years of experience usually initiate calls at the early stages of the sales cycle to qualify leads for both B2B and B2C. This changes during the lead/opportunity management stage, when leads start requesting information, appointments, and demos. At this point, the lead is usually passed on to a more experienced salesperson. Experienced salespeople would have familiarized themselves overtime with a variety of selling scenarios and customer types (Giacobbe et al., 2006; Verbeke et al., 2011), hence, they know the dos and don’ts during interactions with leads.

Engage Every day and Every time

The reality remains that the best day and time to call leads is just a sales myth that must be obliterated. We found that every day and time has the potential to result in a Win outcome with leads. However, we did find some notable trends that are important to highlight. We found that weekends are not the best days to call B2B or B2C leads for qualification, and evenings are not ideal for calling B2B leads during the lead qualification stage. This means that leads usually do not want to have conversations to be qualified on their non-working hours. Conversely, we found that during the lead/opportunity management, there is a significant increase in Win outcomes for B2B leads contacted on weekends or evenings. We suspect that weekend or evening calls with Win outcomes are callbacks requested by the leads themselves for a specific time and day. Ideally, after a live contact has been made with a qualified lead, subsequent contacts with the lead are driven by callback time preferences specified by the lead.

Prioritize your Web leads

Our findings do reaffirm that Web leads matter to a great deal to Win outcomes. Typically, salespeople must initiate contacts with leads first and confirm their needs and requirements for a product or service. However, when a lead completes a webform or downloads digital documents form a vendor's website (i.e., becomes a Web lead), it has, by default, confirmed an interest in the vendor's product or service. Thus, salespeople should always prioritize Web leads for contact, particularly during the lead/opportunity management stage. Also, we encourage inside sales practitioners to provide online capabilities for leads to be able to complete inquiries and download resources. Sales practitioners should pay attention to marketing-sales collaborations in their continuous effort to create awareness of their product and service offerings which can help drive leads to their websites.

Industry, Population Size and Average Income are Potential Moderators

We found that the IT and Financial services industries have better Win outcomes than Insurance and Marketing and Advertising industries during lead qualification. We suspect this may be because most IT and Financial services organizations are primary adaptors of the inside selling model and have overtime implemented the right strategies such as creating online capabilities that help generate Web leads with better conversion chances. Nevertheless, it should be noted that the overall impact of Industry on Win outcomes decreases during the lead/opportunity management stages.

Furthermore, we used population size and the average income of the location (i.e., zip code) of B2C leads to assess if these two predictors could impact lead conversion outcomes. We found that Win outcome was consistent across all population sizes and average income levels. We believe this may be because we use average indicators of the lead's location. We argue that data about a specific lead's income level would probably show a different outcome in the analysis.

6.5.2. Research Contributions

The findings of this study carry significant contributions for both theory and practice in the emerging field of inside sales.

Foremost, this is the first empirically grounded study to explicitly explore sales lead engagement variables that conceptualize salesperson effort (i.e., average number of calls, contact attempts per lead), salesperson performance (i.e., Ratio of Win leads), salesperson experience, call duration, days to lead, sales cycle time, call time, call day, company business model, industry and lead location. To the best of our knowledge, no academic research has explored this range of variables and data size generated through the interactions of inside salespeople with leads in a single study. By investigating these lead engagement factors, we answer the call to research on "*how machine learning and AI [can] help develop systems that recommend customer engagement strategies based on analysis of past engagements and their success/failure and depending on salesperson, industry and customer*" (Syam & Sharma, 2018, p. 141). We reveal that salesperson performance, call duration, industry, salesperson effort, emails, days to lead and lead type are significant predictors of Win outcomes during lead qualification and lead/opportunity management.

Secondly, to the best of our knowledge, this is the first work that provides interpretable, explainable, and comprehensible insights on the best lead engagement practices. We identified several predictor variables and shared insights on their relevance across stages of the sales pipeline (i.e., Lead Qualification and Lead/opportunity management stages) in B2B and B2C settings. These insights can serve as guidelines that may help sales practitioners identify salespeople's skills and behaviors and coaching and skill development strategies that are effective for lead engagement at the lead qualification and lead/opportunity management stages of the sales pipeline. While most of our findings are in line with existing arguments in the literature, some counterintuitive findings contradict some industrial norms. For instance, we show that contrary to what practitioners believe, there is no such thing as a single best day and time to call leads. Nonetheless, our lead conversion model that integrates industry-specific performance of salespeople, characteristics of leads and lead engagement factors can be deployed by any inside selling company that offers similar industrial services to optimize their lead/opportunity management practices and ultimately improve sales success.

Furthermore, previous research has implemented either (1) Black box ML methods that arguably provide the best model performance but offer explanations that are sometimes not reliable and misleading (Rudin, 2019), or (2) interpretable ML methods that provide average model performance but offer useful explanations on patterns that exist in the data. Our methodology provides a unique insight on how to combine ML methods that are inherently interpretable and explainable and ML methods that use other methods to explain their outputs. Also, it should be noted that the large size of the dataset used in our research is the first of its kind in the emerging field of inside sales.

6.5.3. Limitations and Further Research

Although this study delivers some counter-intuitive insights on effective lead/opportunity management strategies and practices, it has some limitations that provide openings for further research. First, the majority (94.1%) of leads are from the United States. This may have an impact on the generalizability of our findings globally. Accordingly, we urge forthcoming research to explore alternative datasets that can be used to draw conclusions that are globally valid. Second, the applicability of the models (hence the insights) suggested in this study are limited to service industries. While narrowing the scope of our study helped manage possible confounding factors, it limited the generalizability of the results to service industries. Finally, we did not explore the impact of several individual lead characteristics (e.g., gender, age, number of employees, etc.) that can be leveraged to build specific lead profiles, which may help practitioners understand how best to engage with specific leads. This offers a unique opportunity to enrich prior literature on lead profiling and its application in lead engagement.

Table 6.1: Application of Machine Learning in the Sales Pipeline

Sales Pipeline Stage	Source	Outcome Measure	Blackbox Solution	Selected Algorithms	Contribution
Lead qualification	D'Haen and Van den Poel (2013)	Ranked list of qualified prospects	■	Clustering and Decision tree	A three-stage model to identify qualified leads who are likely to convert to customers.
	D'Haen *et al.* (2016)	Ranked list of qualified prospects	■	A combination of Text analysis, Latent semantic analysis, Spherical clustering and Logistic regression.	A lead qualification framework that crawls the web for information about prospects.
	Gokhale and Joshi (2017)	Yes (i.e., Qualified) or No (i.e., Not Qualified)	■	Two-Class Logistic Regression; Two-Class Boosted Decision Tree; Two-Class Neural Network; Two-class decision forest	A framework to automate the lead identification and qualification process using machine learning models.
	Nygård and Mezei (2020)	Purchase likelihood of leads	■	Random forest	A lead scoring model to support salespeople while pursuing leads.
Lead and opportunity management	Yan *et al.* (2015)	Won or Lost	■	Logistic Regression	A machine learning based unified framework for sales opportunity win propensity.
	Bohanec *et al.* (2016)	Won or Lost		Random forest, with IME method and Explained Prediction	A general explanation methodology for machine learning models in B2B sales forecasting.
	Bohanec *et al.* (2017)	Won or Lost		Random forest, with Explain and method	A learning and explanation model for B2B sales forecasting.
	Mortensen *et al.* (2019)	Won or Lost	■	Random Forest	A model to predict win propensities for individual sales opportunities.
End-to-end	Megahed *et al.* (2016)	Win ratio	■	Weighted average	A multi-stage sales pipeline maturity model for predicting sales opportunity outcomes.
	Xu *et al.* (2017)	Win ratio and Revenue estimation	■	Seasonal ARIMA, Linear/Exponential regression and Neural Network	A model for forecasting lead conversion ratio and revenue estimation which can be applicable to different sales designs, products or service and teams.
	Eitle and Buxmann (2019)	Won or Lost	■	CatBoost; Random Forest algorithm	A sales pipeline end-to-end process model for the software industry

Table 6.2: Variable Description

Data Name	Data Type	Description
Call History ID	Numeric	A unique identifier key for a call made
Contact ID	Numeric	A unique identifier key for a lead
Industry	Category	The industry the sale organization represents
Country	Category	The country of the lead
Lead Type	Category	Specifies if the lead is a Web lead or a Non-web lead
Cycle Time	Numeric	The number of days the lead has been in the sales funnel. This was computed using the difference between dates a lead was first contacted and the current day of the call to the lead.
Duration	Numeric	The amount of time spent on call with each lead (recorded in minutes). The boundaries are defined as follows: 0 to 1 minute: Short 1 to 10 minutes: Moderate Over 10 minutes: Long
Salesperson Effort (i.e., Contact Attempt)	Numeric	The number of interactions attempt with a lead (i.e., Interaction attempt number)
Salesperson Effort (i.e., Average Number of Calls)	Numeric	The number calls made by a salesperson makes in a day. To create the *average number of calls* variable, this study grouped individual salespersons by call dates to get the total number of days they worked. Then, the total number of calls made by each salesperson is computed. Finally, the total number of calls made is divided by days worked get average number of calls per day for each salesperson.
Salesperson Performance	Numeric	The ratio of won leads for the salesperson. The boundaries are defined as follows: 0 to 5%: Low 5 to 15%: Medium Over 20%: High
Salesperson Experience	Numeric	The minimum number of days of experience working in sales, with the current company and in the current territory. We computed the *salesperson experience* using the difference between when an account was created for an individual salesperson's and when the instant of a sales call was made by that salesperson.
Business model	Category	Specifies if the lead is a business (i.e., B2B) or customer (i.e., B2C).
Weekday	Category	The day of call to the lead
Call Time	Category	The time of call to the lead. The boundaries are defined as follows: 0800 to 1200: Morning 1200 to 1600: Afternoon 1600 to 2000: Evening
Email Size	Numeric	The number of characters in the email sent to the lead. The boundaries are defined as follows: 1 to 500 characters: Small 500 to 5000 characters: Medium Over 5000 characters: Large
Email Response	Category	The status (i.e., opened or closed) of the email sent to the lead
Call Outcome	Category	The result of call made to the lead (i.e., Unknown, Loss and Won).

Average Income by Zip code	Numeric	The average household income of the zip code the lead resides in
Average population by Zip code	Numeric	The average population of the zip code the lead resides in
Sales pipeline Stages	Category	The stage of the pipeline the lead currently is based on the interaction outcome

Table 6.3: Dataset Summary

Summary Data for all Interactions			Summary Data for all Leads		
Business Model Type	**Count**	**%**	**Business Model Type**	**Count**	**%**
B2B	24,401,535	64.5%	B2B	5,147,446	68.6%
B2C	13,457,706	35.5%	B2C	2,355,896	31.4%
Total	**37,859,241**		**Total**	**7,503,342**	
Country	**Count**	**%**	**Country**	**Count**	**%**
USA	36,724,375	97%	USA	7,058,335	94.1%
RoW	1,134,830	3%	RoW	445,007	5.9%
Total	**37,859,241**		**Total**	**7,503,342**	
Lead Type	**Count**	**%**	**Lead Type**	**Count**	**%**
Non-web lead	24,048,285	63.5%	Non-web lead	5,684,199	75.8%
Web lead	13,810,955	36.5%	Web lead	1,819,143	24.2%
Total	**37,859,241**		**Total**	**7,503,342**	
Industry	**Count**	**%**	**Industry**	**Count**	**%**
Financial Services	8,403,764	22.2%	Financial Services	1,624,960	21.7%
Insurance	18,149,937	47.9%	Insurance	3,066,266	40.9%
IT Services	3,810,160	10.1%	IT Services	695,329	9.3%
Marketing & Advertising	7,495,385	19.8%	Marketing & Advertising	2,116,787	28.2%
Total	**37,859,241**		**Total**	**7,503,342**	
Interaction Distribution in Stages	**Count**	**%**	**Lead Distribution in Stages**	**Count**	**%**
No Contact	22,253,139	58.8%	No Contact	2,098,626	28.0%
Lead Generation	69,045	0.2%	Lead Generation	16,393	0.2%
Lead/Opportunity Management	1,178,965	3.1%	Lead/Opportunity Management	332,557	4.4%
Lead Qualification	14,358,092	37.9%	Lead Qualification	5,055,766	67.4%
Total	**37,859,241**		**Total**	**7,503,342**	
Interaction Outcomes	**Count**	**%**	**Final Lead Outcome**	**Count**	**%**
Loss	8,763,527	23.1%	Loss	5,564,832	74.2%
Unknown	26,138,885	69.0%	Unknown	1,057,325	14.1%
Win	2,956,829	7.8%	Win	881,185	11.7%
Total	**37,859,241**		**Total**	**7,503,342**	

Table 6.4: Lead Qualification Model Performance

Lead Qualification B2B Models	Training Data Size	CA	Sensitivity	Specificity	F-Measure	BA	G-mean
CART Baseline	5,608,119	93.1%	74.1%	97.2%	79.2%	85.7%	84.9%
CART Oversampling	9,224,096	88.9%	89.7%	88.7%	74.2%	89.2%	89.2%
CART Under sampling	1,660,118	88.9%	89.7%	88.8%	74.2%	89.2%	89.2%
CART SMOTE	2,374,085	89.8%	88.7%	90.0%	75.5%	89.4%	89.4%
LR Baseline	5,608,119	92.4%	68.5%	97.5%	76.1%	83.0%	81.7%
LR Oversampling	9,224,096	91.6%	84.8%	93.0%	78.1%	88.9%	88.8%
LR Under sampling	1,660,118	91.6%	84.8%	93.0%	78.1%	88.9%	88.8%
LR SMOTE	2,374,085	92.1%	81.3%	94.4%	78.5%	87.8%	87.6%
NB Baseline	5,608,119	76.3%	85.5%	74.3%	56.2%	79.9%	79.7%
NB Oversampling	9,224,096	68.3%	90.4%	63.5%	50.3%	76.9%	75.7%
NB Under sampling	1,660,118	68.4%	90.3%	63.7%	50.4%	77.0%	75.8%
NB SMOTE	2,374,085	69.6%	89.7%	65.3%	51.2%	77.5%	76.5%
RF Baseline	5,608,119	95.7%	85.4%	97.9%	87.7%	91.7%	91.5%
RF Oversampling	9,224,096	95.1%	93.8%	95.4%	87.3%	94.6%	94.6%
RF Under sampling	1,660,118	94.1%	95.2%	93.9%	85.2%	94.6%	94.6%
RF SMOTE	2,374,085	94.8%	93.4%	95.2%	86.6%	94.3%	94.3%
Lead Qualification B2C Models	**Training Data Size**	**CA**	**Sensitivity**	**Specificity**	**F-Measure**	**BA**	**G-mean**
CART Baseline	3,048,168	94.9%	45.5%	98.8%	56.4%	72.1%	67.0%
CART Oversampling	5,653,912	87.9%	87.5%	87.9%	51.2%	87.7%	87.7%
CART Under sampling	442,416	87.9%	87.5%	87.9%	51.2%	87.7%	87.7%
CART SMOTE	1,290,380	89.2%	86.5%	89.4%	53.8%	88.0%	87.9%
LR Baseline	3,048,168	94.2%	34.3%	98.8%	46.0%	66.6%	58.2%
LR Oversampling	5,653,912	89.0%	69.6%	90.5%	47.8%	80.1%	79.4%
LR Under sampling	442,416	89.0%	69.7%	90.5%	47.8%	80.1%	79.4%
LR SMOTE	1,290,380	89.8%	63.7%	91.8%	47.5%	77.7%	76.5%
NB Baseline	3,048,168	85.1%	55.4%	87.4%	35.1%	71.3%	69.6%
NB Oversampling	5,653,912	83.1%	57.6%	85.1%	33.1%	71.4%	70.0%
NB Under sampling	442,416	83.1%	57.6%	85.1%	33.1%	71.3%	70.0%
NB SMOTE	1,290,380	83.3%	57.3%	85.4%	33.3%	71.4%	70.0%
RF Baseline	3,048,168	96.6%	67.8%	98.9%	74.5%	83.4%	81.9%
RF Oversampling	5,653,912	96.2%	83.3%	97.2%	75.9%	90.2%	90.0%
RF Under sampling	442,416	92.6%	93.3%	92.6%	64.7%	92.9%	92.9%
RF SMOTE	1,290,380	95.0%	88.3%	95.5%	71.9%	91.9%	91.9%

Table 6.5: Lead Qualification CART Predictor Variable Importance

B2B Model		B2C Model	
Predictor Variables	**Importance Score**	**Predictor Variables**	**Importance Score**
Salesperson Performance	100.00	Salesperson Performance	100.00
Financial Service Industry	22.39	Insurance Industry	39.42
Insurance Industry	21.01	Call Duration	38.72
Contact Attempt	17.97	Financial Service Industry	34.73
Sales Cycle Time	12.43	Average Number of Calls	34.40
Call Duration	9.56	Email Size	6.10
Email Sent	3.35	Contact Attempt	2.92
Email Size	2.79	Web Lead	2.59
Web Lead	2.32	Salesperson Experience	1.96
Average Number of Calls	1.39	Email Sent	1.10
IT Service Industry	0.28	Days to lead	1.02
Days to lead	0.07	Manual Email Source	0.65

Table 6.6: Lead Qualification LR Model Path Coefficients

Predictor Variables	B	SE	z-value	Predictor Variables	B	SE	z-value
(Intercept)	-2.01*	0.01	-212.80	(Intercept)	-1.99*	0.04	-46.00
Salesperson Performance	10.93*	0.02	464.86	Salesperson Performance	8.63*	0.05	158.36
Email Sent	1.77*	0.01	156.87	IT Service Industry	1.35*	0.06	20.83
IT Service Industry	0.74*	0.01	103.66	Financial Service Industry	1.21*	0.04	30.02
Financial Service Industry	0.57*	0.01	81.84	Insurance Industry	1.03*	0.04	25.50
Email Response	0.12*	0.01	8.24	Salesperson Experience	0.38*	0.01	67.79
Salesperson Experience	0.10*	0.00	52.28	Email Response	0.34*	0.02	14.25
Call Duration	0.10*	0.00	203.39	Web Lead	0.11*	0.01	8.83
Friday Call	0.03*	0.01	3.99	Evening Call	0.08*	0.01	7.07
Contact Attempt	0.02*	0.00	97.73	Call Duration	0.06*	0.00	74.54
Sunday Call	0.00ns	0.04	0.11	Tuesday Call	0.05*	0.01	3.93
Monday Call	0.00ns	0.01	0.38	Monday Call	0.05*	0.01	3.61
Thursday Call	0.00ns	0.01	0.04	Thursday Call	0.01ns	0.01	0.80
Days to lead	0.00*	0.00	12.38	Sales Cycle Time	0.00*	0.00	9.68
Email Size	-0.00*	0.00	-12.54	Population Size	-0.00*	0.00	-7.99
Sales Cycle Time	-0.00*	0.00	-38.63	Average Income	-0.00*	0.00	-18.88
Average Number of Calls	-0.00*	0.00	-96.40	Email Size	-0.00*	0.00	-9.35
Tuesday Call	-0.02**	0.01	-2.60	Average Number of Calls	-0.00*	0.00	-10.65
Afternoon Call	-0.02**	0.01	-3.71	Days to lead	-0.00*	0.00	-23.85
Evening Call	-0.07*	0.01	-8.51	Friday Call	-0.01ns	0.02	-0.67
Manual Email Source	-0.66*	0.01	-46.93	Contact Attempt	-0.02*	0.00	-27.52
Insurance Industry	-0.79*	0.01	-74.54	Afternoon Call	-0.03**	0.01	-3.06
Saturday Call	-0.82*	0.03	-27.67	Saturday Call	-0.12*	0.02	-5.85
Web Lead	-1.24*	0.01	-102.98	Sunday Call	-0.18*	0.03	-6.85
Wednesday Call	NA	NA	NA	Email Sent	-0.19*	0.02	-9.61
Morning Call	NA	NA	NA	Manual Email Source	-0.82*	0.02	-38.86
Marketing & Advertising Industry	NA	NA	NA	Wednesday Call	NA	NA	NA
				Morning Call	NA	NA	NA
				Marketing & Advertising Industry	NA	NA	NA

Significant at 1% = “*”; Significant at 5% = “**”; Not Significant = “ns”

Table 6.7: Lead & Opportunity Management Model Performance

Lead & Opportunity Management B2B Models	Training Data Size	CA	Sensitivity	Specificity	F-Measure	BA	G-mean
CART Baseline	506,120	90.7%	96.9%	67.7%	94.3%	82.3%	81.0%
CART Oversampling	798,624	86.7%	88.8%	78.6%	91.3%	83.7%	83.6%
CART Under sampling	213,616	86.0%	87.1%	82.2%	90.8%	84.6%	84.6%
CART SMOTE	747,656	87.8%	90.8%	76.5%	92.1%	83.7%	83.3%
LR Baseline	506,120	86.7%	95.3%	54.3%	91.9%	74.8%	72.0%
LR Oversampling	798,624	79.6%	79.8%	78.9%	86.1%	79.4%	79.3%
LR Under sampling	213,616	79.6%	79.8%	78.9%	86.1%	79.4%	79.4%
LR SMOTE	747,656	83.0%	85.7%	72.7%	88.8%	79.2%	78.9%
NB Baseline	506,120	81.0%	84.7%	67.3%	87.6%	76.0%	75.5%
NB Oversampling	798,624	74.3%	74.6%	73.1%	82.1%	73.8%	73.8%
NB Under sampling	213,616	75.9%	77.2%	71.2%	83.5%	74.2%	74.1%
NB SMOTE	747,656	75.2%	76.0%	72.4%	82.9%	74.2%	74.2%
RF Baseline	506,120	96.5%	98.8%	87.9%	97.8%	93.3%	93.2%
RF Oversampling	798,624	96.5%	98.3%	90.2%	97.8%	94.2%	94.1%
RF Under sampling	213,616	95.2%	95.4%	94.2%	96.9%	94.8%	94.8%
RF SMOTE	747,656	96.1%	97.2%	91.9%	97.5%	94.6%	94.5%
Lead & Opportunity Management B2C Models	**Training Data Size**	**CA**	**Sensitivity**	**Specificity**	**F-Measure**	**BA**	**G-mean**
CART Baseline	319,158	94.6%	98.2%	81.4%	96.6%	89.8%	89.4%
CART Oversampling	500,622	92.3%	92.5%	91.4%	95.0%	92.0%	92.0%
CART Under sampling	137,694	92.7%	93.4%	90.2%	95.2%	91.8%	91.8%
CART SMOTE	481,929	93.4%	94.4%	89.6%	95.7%	92.0%	92.0%
LR Baseline	319,158	90.5%	96.2%	69.6%	94.1%	82.9%	81.8%
LR Oversampling	500,622	86.5%	86.9%	85.1%	91.0%	86.0%	86.0%
LR Under sampling	137,694	86.4%	86.8%	85.0%	90.9%	85.9%	85.9%
LR SMOTE	481,929	88.5%	90.2%	82.2%	92.5%	86.2%	86.1%
NB Baseline	319,158	79.7%	79.1%	81.9%	86.0%	80.5%	80.5%
NB Oversampling	500,622	73.9%	69.8%	88.8%	80.8%	79.3%	78.7%
NB Under sampling	137,694	73.5%	69.2%	89.1%	80.3%	79.1%	78.5%
NB SMOTE	481,929	73.5%	69.1%	89.5%	80.4%	79.3%	78.6%
RF Baseline	319,158	98.3%	99.4%	94.2%	98.9%	96.8%	96.8%
RF Oversampling	500,622	98.4%	99.1%	95.7%	99.0%	97.4%	97.4%
RF Under sampling	137,694	97.3%	97.4%	96.9%	98.3%	97.2%	97.2%
RF SMOTE	481,929	97.7%	98.2%	96.0%	98.5%	97.1%	97.1%

Table 6.8: Lead/Opportunity Management CART Predictor Variable Importance

B2B Model		B2C Model	
Predictor Variables	**Importance Score**	**Predictor Variables**	**Importance Score**
Manual Email Source	100.00	Salesperson Performance	100
Email Size	86.08	Email Size	77.62
Call Duration	83.76	Call Duration	73.53
Salesperson Performance	77.09	Manual Email Source	72.00
Email Sent	56.35	Email Sent	63.65
Average Number of Calls	31.46	Average Number of Calls	6.01
Days to lead	22.36	Salesperson Experience	4.95
Web Lead	16.66	Sales Cycle Time	4.51
Marketing & Advertising Industry	11.16	Days to lead	3.43
Sales Cycle Time	6.61	Contact Attempt	2.90
Insurance Industry	4.99	Financial Service Industry	1.55
Financial Service Industry	3.68	Insurance Industry	0.55
IT Service Industry	3.15		
Email Response	1.92		
Contact Attempt	1.36		
Saturday Call	0.79		
Salesperson Experience	0.38		

Table 6.9: Lead/Opportunity Management LR Model Path Coefficients

B2B Model				B2C Model			
Predictor Variables	**B**	**SE**	**z-value**	**Predictor Variables**	**B**	**SE**	**z-value**
(Intercept)	-1.24*	0.01	-118.96	(Intercept)	-3.24*	0.05	-65.28
Salesperson Performance	4.09*	0.02	217.51	Salesperson Performance	15.22*	0.13	121.17
Saturday Call	1.86*	0.03	73.36	Insurance Industry	3.60*	0.05	77.74
Web Lead	0.74*	0.01	62.97	IT Service Industry	1.93*	0.10	18.54
Evening Call	0.70*	0.01	81.58	Salesperson Experience	0.72*	0.01	89.19
Financial Service Industry	0.42*	0.01	52.72	Email Response	0.24*	0.02	13.93
Insurance Industry	0.37*	0.01	33.34	Monday Call	0.15*	0.01	10.04
Email Response	0.34*	0.01	34.26	Call Duration	0.15*	0.00	122.76
IT Service Industry	0.34*	0.01	31.37	Friday Call	0.09*	0.02	5.46
Friday Call	0.24*	0.01	25.33	Tuesday Call	0.07*	0.01	4.44
Afternoon Call	0.20*	0.01	31.03	Web Lead	0.01ns	0.01	0.98
Sunday Call	0.17*	0.04	4.77	Days to lead	0.00*	0.00	37.09
Call Duration	0.10*	0.00	231.22	Average Number of Calls	0.00*	0.00	37.68
Salesperson Experience	0.01*	0.00	3.81	Email Size	0.00ns	0.00	0.44
Monday Call	0.00ns	0.01	0.18	Average Income	0.00ns	0.00	1.01
Average Number of Calls	0.00*	0.00	23.00	Population Size	0.00*	0.00	-8.94
Sales Cycle Time	0.00*	0.00	49.96	Sales Cycle Time	-0.01*	0.00	-52.28
Days to lead	0.00*	0.00	28.97	Thursday Call	-0.03ns	0.01	-1.85
Email Size	-0.00*	0.00	-164.89	Contact Attempt	-0.05*	0.00	-123.82
Thursday Call	-0.01ns	0.01	-20.31	Financial Service Industry	-0.06ns	0.06	-0.99
Contact Attempt	-0.03*	0.00	-4.29	Evening Call	-0.08*	0.01	-7.30
Tuesday Call	-0.04*	0.01	-100.28	Afternoon Call	-0.14*	0.01	-13.45
Email Sent	-0.21ns	0.01	-1.39	Saturday Call	-0.56*	0.02	-31.19
Manual Email Source	-1.76*	0.01	-17.78	Sunday Call	-0.70*	0.02	-28.84
Wednesday Call	NA	NA	NA	Email Sent	-1.19*	0.02	-72.35
Morning Call	NA	NA	NA	Manual Email Source	-1.56*	0.02	-93.90
Marketing & Advertising Industry	NA	NA	NA	Wednesday Call	NA	NA	NA
				Morning Call	NA	NA	NA
				Marketing & Advertising Industry	NA	NA	NA

Significant at 1% = “*”; Significant at 5% = “**”; Not Significant = “ns”

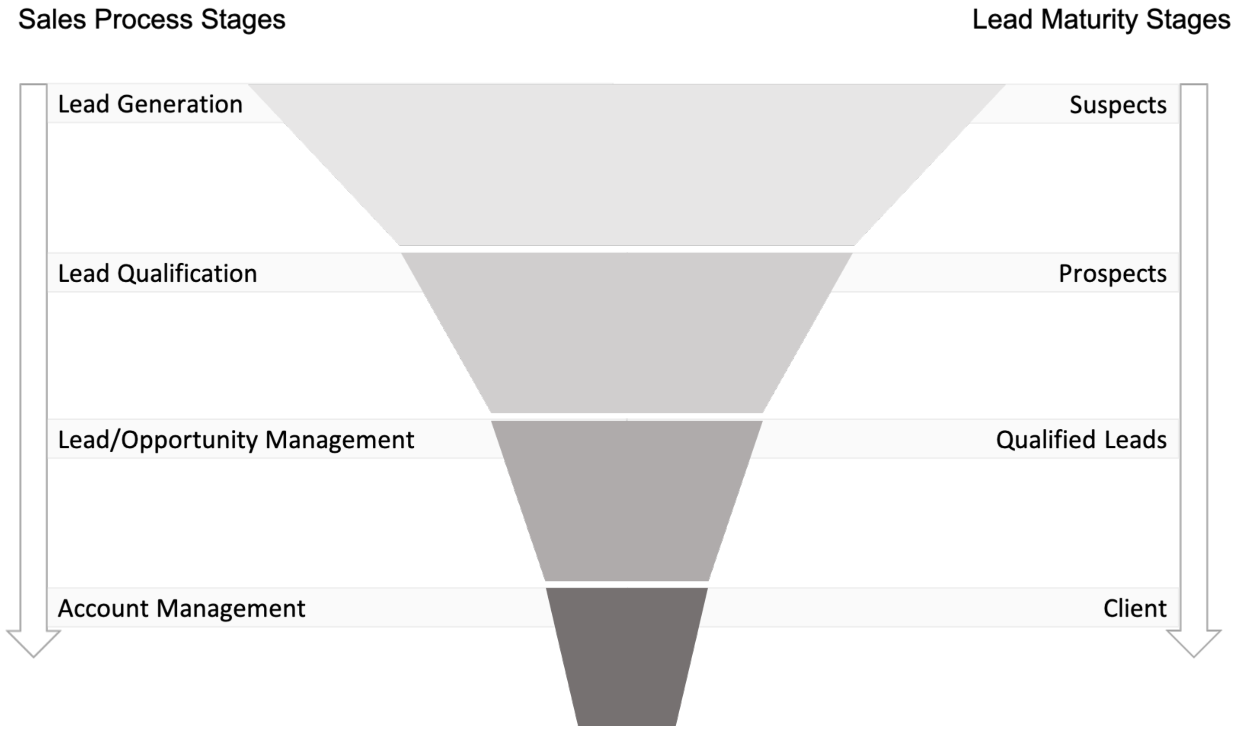

Figure 6.1: Sales Pipeline

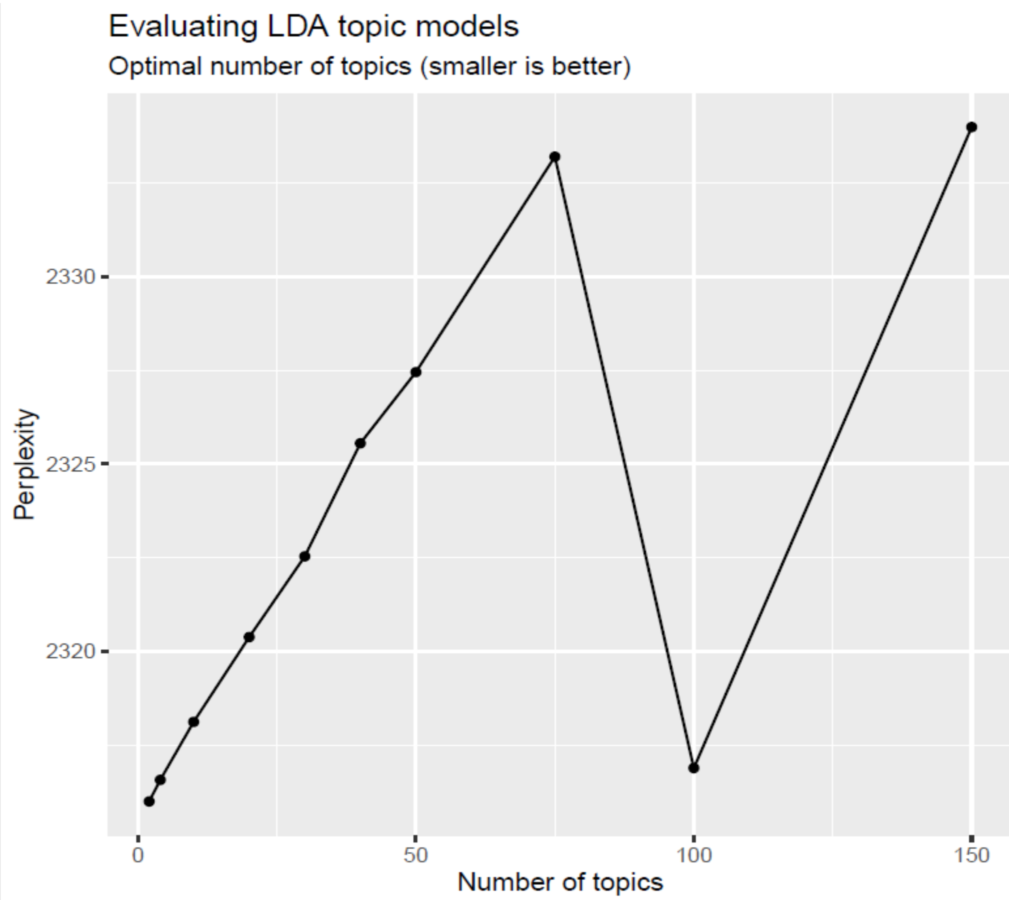

Figure 6.2: Perplexity Optimum Number of Topics

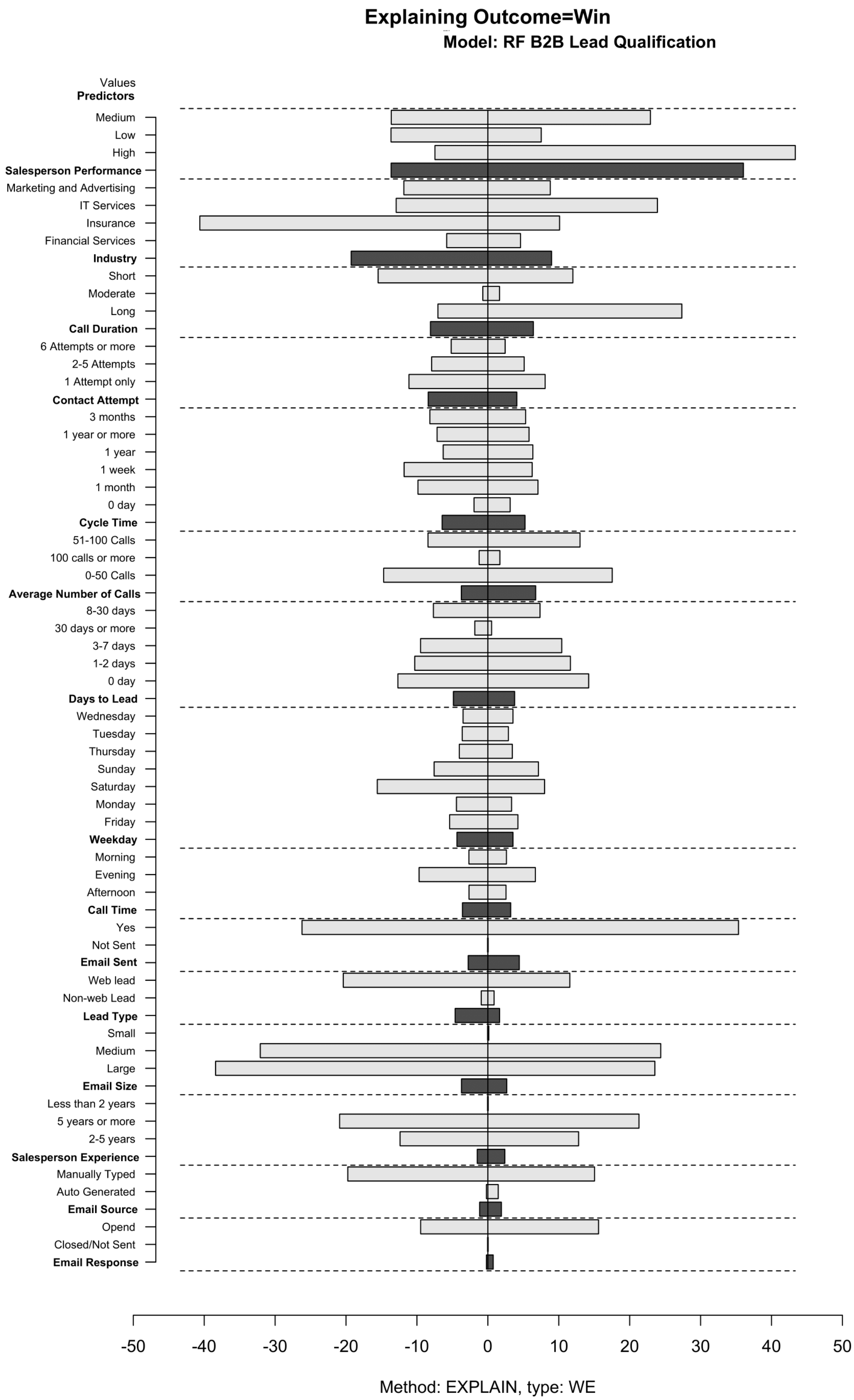

Figure 6.3: RF Model Explanation for B2B Lead Qualification

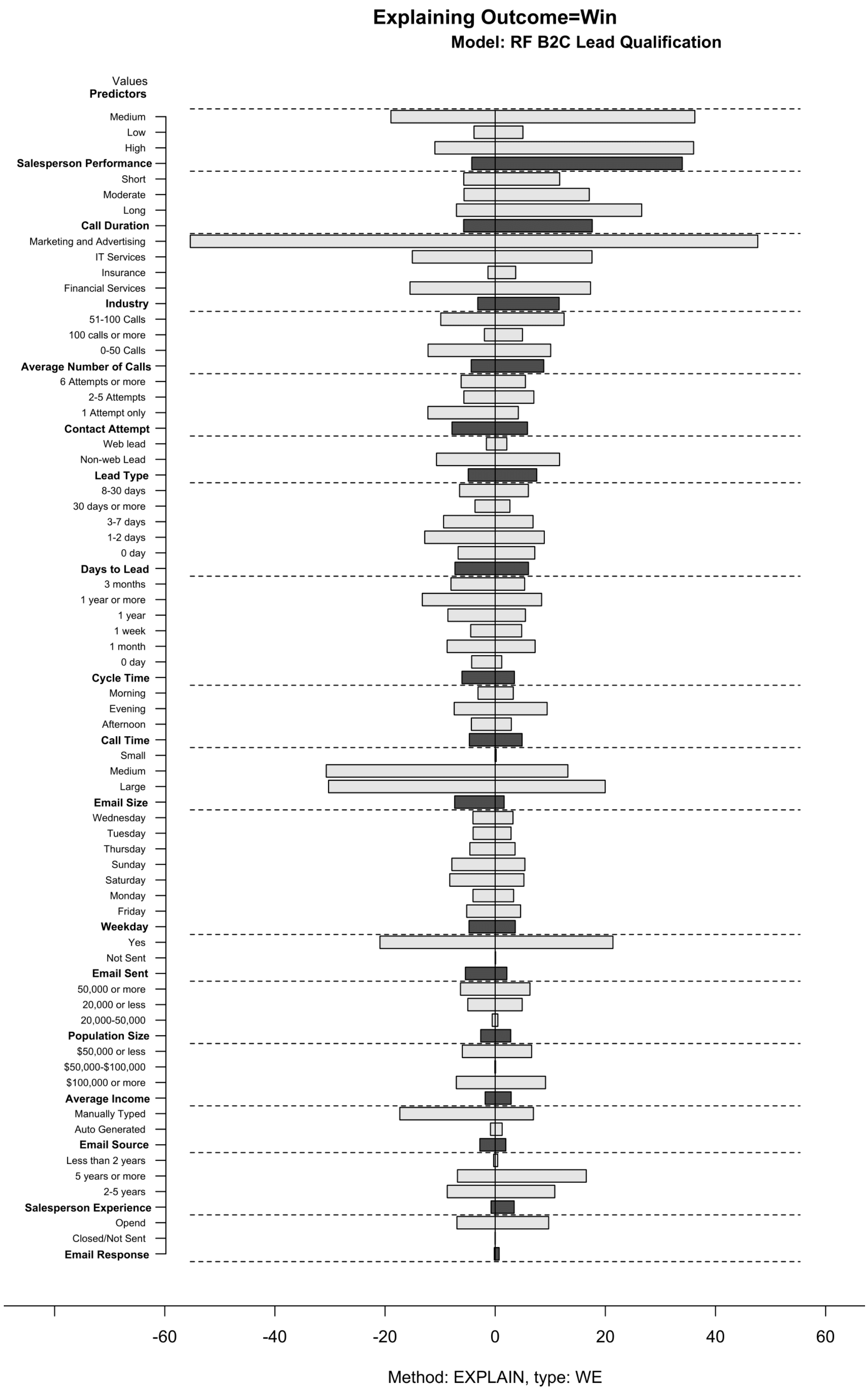

Figure 6.4: RF Model Explanation for B2C Lead Qualification

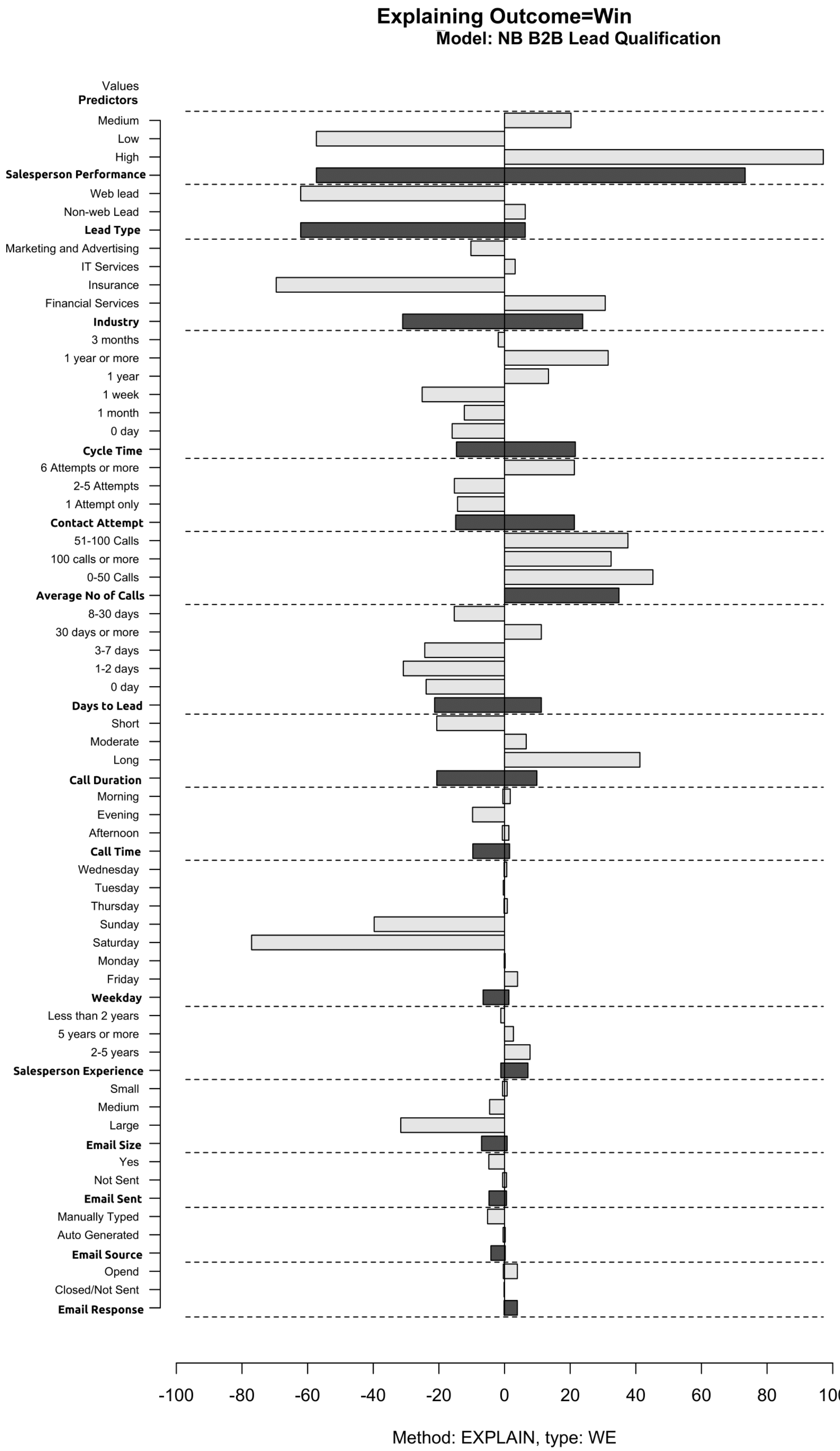

Figure 6.5: NB Model Explanation for B2B Lead Qualification

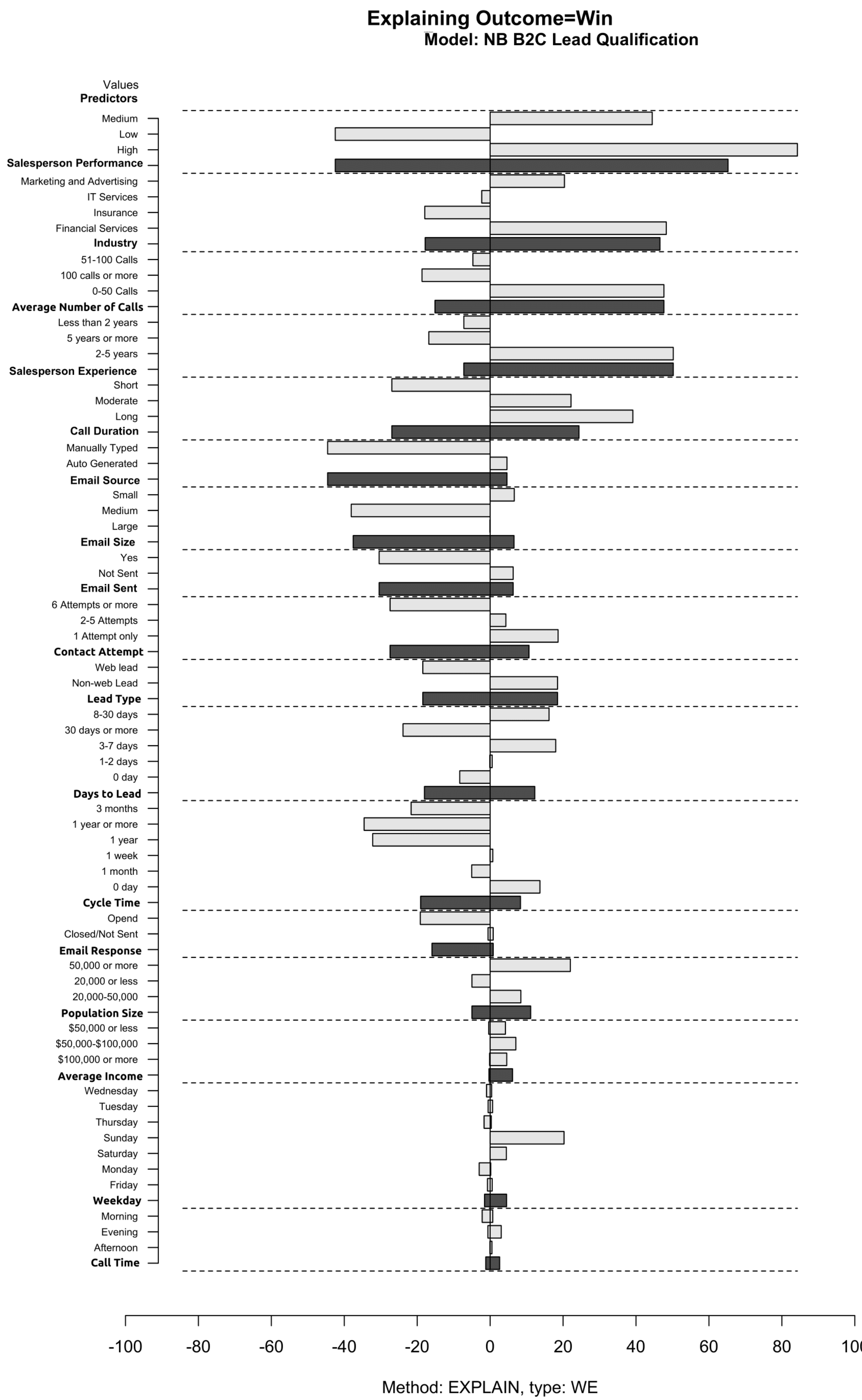

Figure 6.6: NB Model Explanation for B2C Lead Qualification

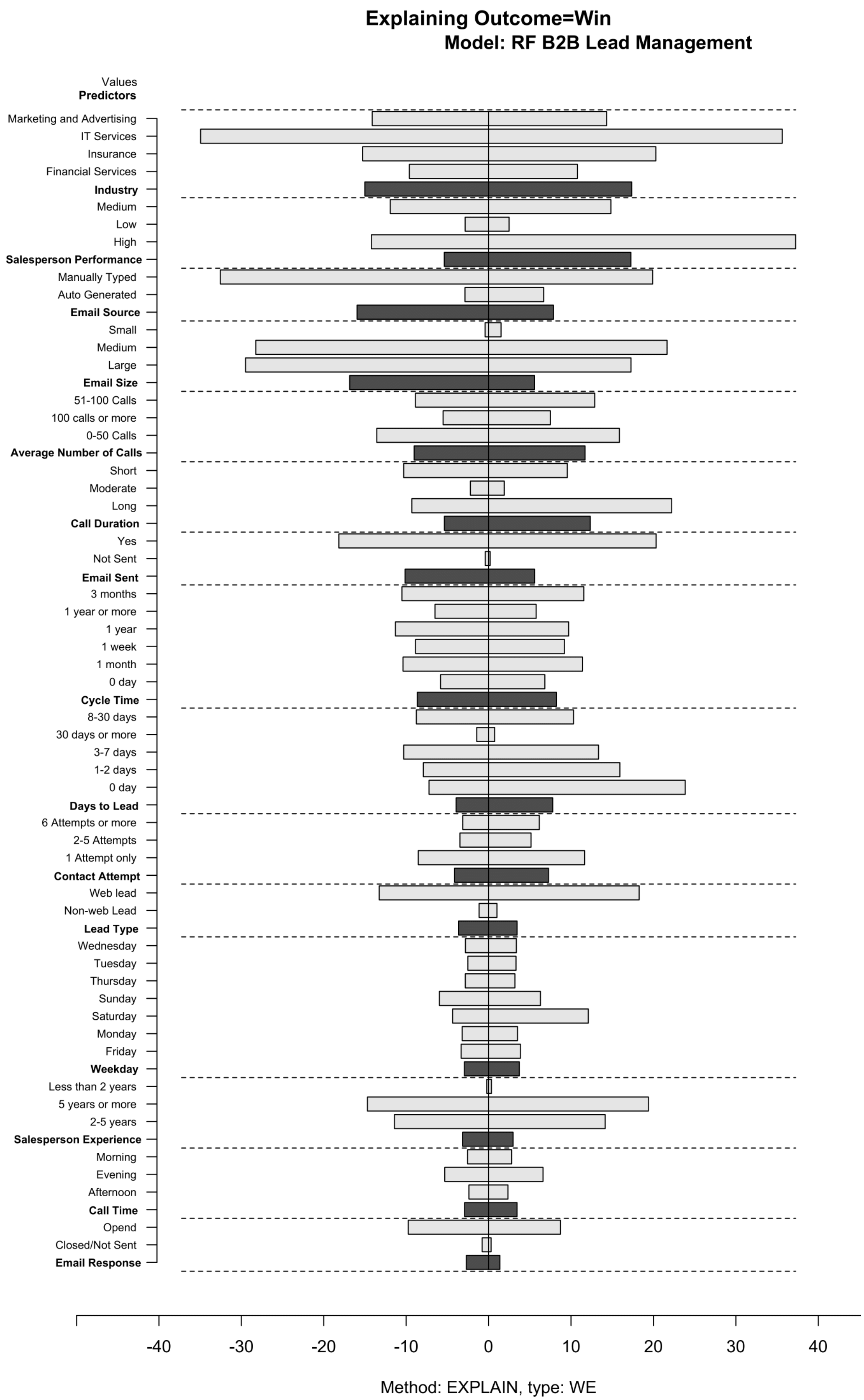

Figure 6.7: RF Model Explanation for B2B Lead/Opportunity Management

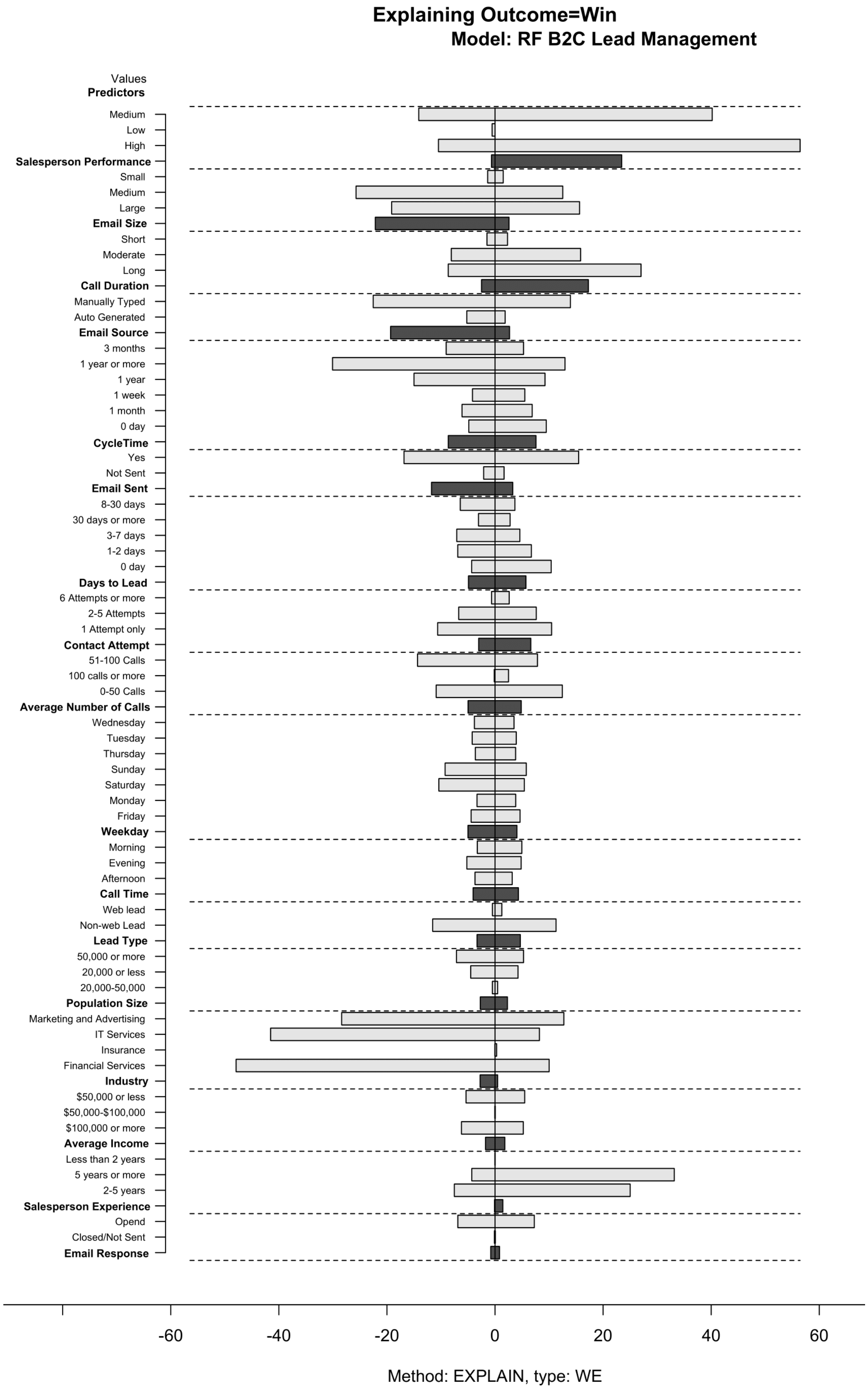

Figure 6.8: RF Model Explanation for B2C Lead/Opportunity Management

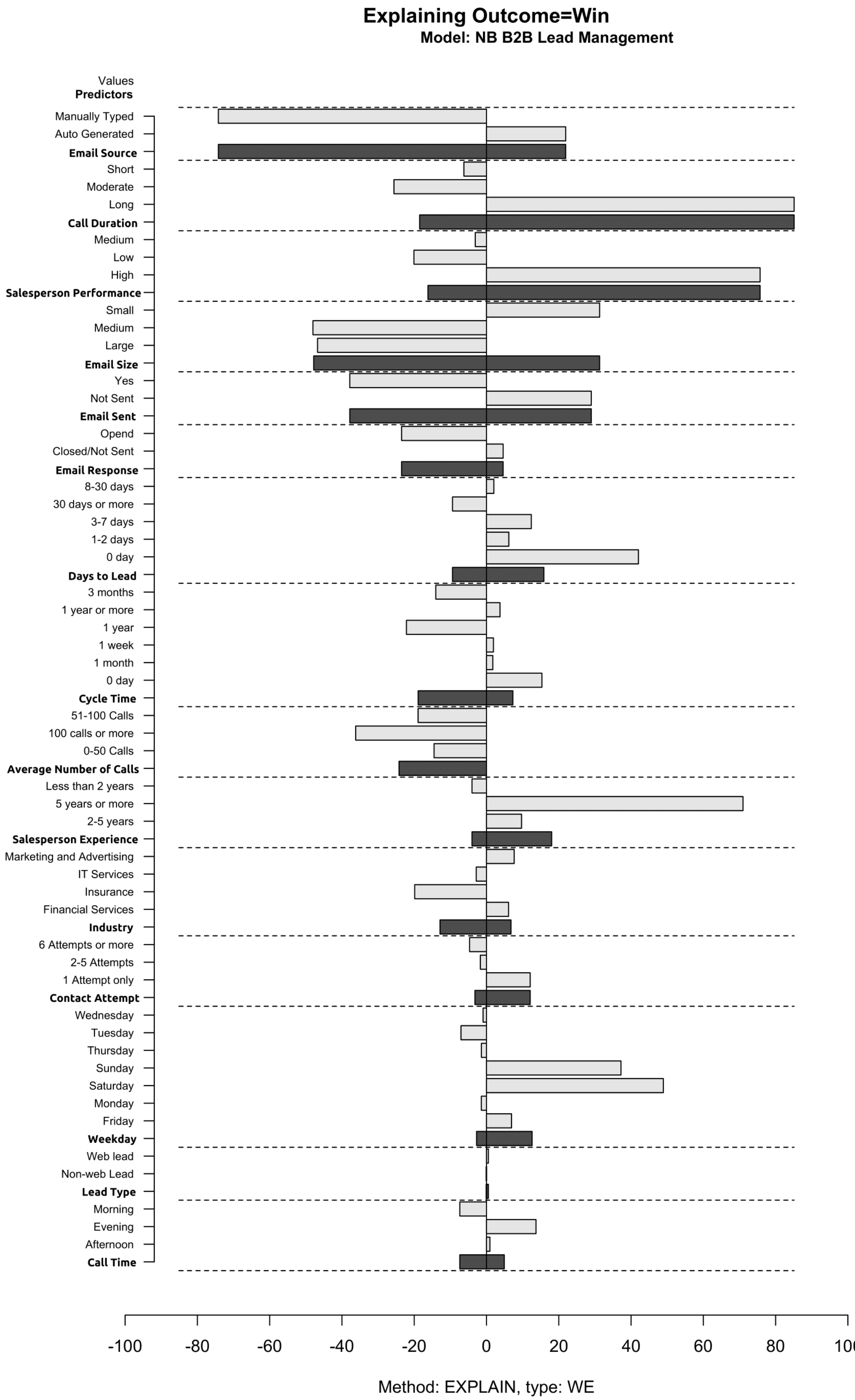

Figure 6.9: NB Model Explanation for B2B Lead/Opportunity Management

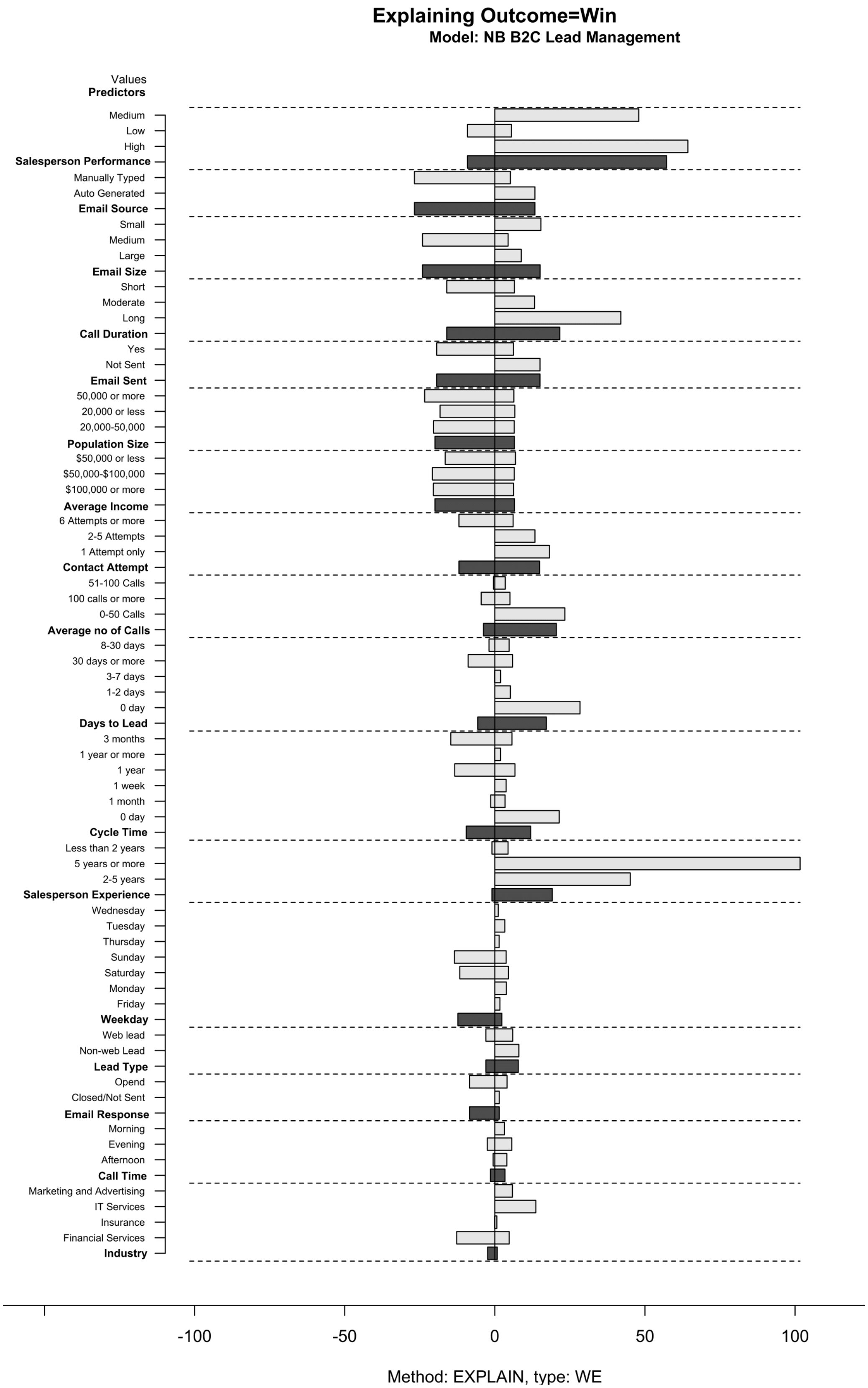

Figure 6.10: NB Model Explanation for B2C Lead/Opportunity Management

References

Abbott, D. (2014). *Applied predictive analytics : principles and techniques for the professional data analyst*.

Akosa, J. (2017). *Predictive Accuracy: A Misleading Performance Measure for Highly Imbalanced Data.* Paper presented at the Proceedings of the SAS Global Forum.

Ang, L., & Buttle, F. (2006). Managing For Successful Customer Acquisition: An Exploration. *Journal of Marketing Management, 22*(3-4), 295-317. doi:10.1362/026725706776861217

Bewick, V., Cheek, L., & Ball, J. (2005). Statistics review 14: Logistic regression. *Critical care, 9*(1), 112.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of machine Learning research, 3*(Jan), 993-1022.

Bohanec, M., Bortnar, M. K., & Robnik-ikonja, M. (2016). Integration of machine learning insights into organizational learning: A case of B2B sales forecasting. 71--85.

Bohanec, M., Bortnar, M. K., & Robnik-ikonja, M. (2017). Explaining machine learning models in sales predictions. *Expert systems with applications, 71*, 416--428.

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.* Paper presented at the 6th International Engaged Management Scholarship Conference.

Breiman, L. (2001). Random forests. *Machine learning, 45*(1), 5-32.

Breiman, L. (2002). Manual on setting up, using, and understanding random forests v3. 1. In (Vol. 1): Statistics Department University of California Berkeley, CA, USA.

Buttle, F. (2009). Managing the customer lifecycle: Customer acquisition. *Customer relationship management: Concepts and technologies*, 225--254.

Cartera, R. E., Hendersonb, C. M., Arronizc, I., & Palmatierd, R. W. (2014). Effect of salespeople's acquisition-retention trade-off on performance. *Journal of Personal Selling and Sales Management, 34*, 91-111. doi:10.1080/08853134.2014.890903

Chawla, N. V. (2005). Data mining for imbalanced datasets: An overview. In *Data mining and knowledge discovery handbook* (pp. 853-867): Springer.

Chuang, J., Roberts, M. E., Stewart, B. M., Weiss, R., Tingley, D., Grimmer, J., & Heer, J. (2015). *TopicCheck: Interactive alignment for assessing topic model stability.* Paper presented at the Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies.

Crawford, S. L. (1989). Extensions to the CART algorithm. *International Journal of Man-Machine Studies, 31*(2), 197-217.

D'Haen, J., & Van den Poel, D. (2013). Model-supported business-to-business prospect prediction based on an iterative customer acquisition framework. *Industrial Marketing Management, 42*(4), 544-551. doi:10.1016/j.indmarman.2013.03.006

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.

Duncan, B. A., & Elkan, C. P. (2015). *Probabilistic modeling of a sales funnel to prioritize leads.* Paper presented at the Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.

Eitle, V., & Buxmann, P. (2019). *Business analytics for sales pipeline management in the software industry: a machine learning perspective.* Paper presented at the Proceedings of the 52nd Hawaii International Conference on System Sciences.

Giacobbe, R. W., Jackson Jr., D. W., 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*, 115-142.

Gokhale, P., & Joshi, P. (2017). *A Binary Classification Approach to Lead Identification and Qualification.* Paper presented at the International Conference on Smart Trends for Information Technology and Computer Communications.

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: .*

He, H., & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on knowledge and data engineering, 21*(9), 1263-1284.

Hunter, G. K., & Perreault, W. D. (2007). Making Sales Technology Effective. *Journal of marketing, 71*, 16-34.

Huysmans, J., Dejaeger, K., Mues, C., Vanthienen, J., & Baesens, B. (2011). An empirical evaluation of the comprehensibility of decision table, tree and rule based predictive models. *Decision Support Systems, 51*(1), 141-154.

Jacobi, C., van Atteveldt, W., & Welbers, K. (2016). Quantitative analysis of large amounts of journalistic texts using topic modelling. *Digital Journalism, 4*(1), 89-106. doi:10.1080/21670811.2015.1093271

Jaramillo, F., & Marshall, G. W. (2004). Critical success factors in the personal selling process: An empirical investigation of Ecuadorian salespeople in the banking industry. *International Journal of Bank Marketing, 22*, 9-25. doi:10.1108/02652320410514906

Jo, T., & Japkowicz, N. (2004). Class imbalances versus small disjuncts. *ACM Sigkdd Explorations Newsletter, 6*(1), 40-49.

Kawas, B., Squillante, M. S., Subramanian, D., & Varshney, K. R. (2013). *Prescriptive analytics for allocating sales teams to opportunities.* Paper presented at the 2013 IEEE 13th International Conference on Data Mining Workshops.

Kohavi, R. (1995). *A study of cross-validation and bootstrap for accuracy estimation and model selection.* Paper presented at the Ijcai.

Kotu, V., & Deshpande, B. (2014). *Predictive analytics and data mining: concepts and practice with rapidminer*: Morgan Kaufmann.

Kubat, M., Holte, R., & Matwin, S. (1997). *Learning when negative examples abound.* Paper presented at the European Conference on Machine Learning.

Łapczyński, M., & Jefmański, B. (2014). Number of Clusters and the Quality of Hybrid Predictive Models in Analytical CRM. *Studies in Logic, Grammar*

Rhetoric, 37(1), 141-157.

Lawrence, S., & Hubbard, A. (2008). Cross-Selling and Up-Selling in the Contact Center. *2008 Aberdeen Group*.

Lee, M., & Wu, T.-C. (2012). An Integral Predictive Model of Financial Distress. *Journal of Testing*

Evaluation, 40(6), 931-938.

Long, M. M., Tellefse, T., & Lichtenthal, J. D. (2007). Internet integration into the industrial selling process: A step-by-step approach. *Industrial Marketing Management, 36*(5), 676--689.

Magee, B., Sammon, D., Nagle, T., & O'Raghallaigh, P. (2016). Introducing data driven practices into sales environments: examining the impact of data visualisation on user engagement and sales results. *Journal of Decision systems, 25*(sup1), 313-328.

Megahed, A., Yin, P., & Nezhad, H. R. M. (2016). *An optimization approach to services sales forecasting in a multi-staged sales pipeline.* Paper presented at the 2016 IEEE International Conference on Services Computing (SCC).

Mohammed, M., Khan, M. B., & Bashier, E. B. M. (2016). *Machine learning: algorithms and applications*: Crc Press.

Monat, J. P. (2011). Industrial sales lead conversion modeling. *Marketing Intelligence & Planning, 29*(2), 178-194.

Mortensen, S., Christison, M., Li, B., Zhu, A., & Venkatesan, R. (2019). *Predicting and Defining B2B Sales Success with Machine Learning.* Paper presented at the 2019 Systems and Information Engineering Design Symposium (SIEDS).

Murphy, K. P. (2012). *Machine learning : a probabilistic perspective*: Cambridge, MA : MIT Press, 2012

©2012.

Napierala, K., & Stefanowski, J. (2012). BRACID: a comprehensive approach to learning rules from imbalanced data. *Journal of Intelligent Information Systems, 39*(2), 335-373.

Nygård, R., & Mezei, J. (2020). *Automating Lead Scoring with Machine Learning: An Experimental Study.* Paper presented at the Proceedings of the 53rd Hawaii International Conference on System Sciences.

Ohiomah, A., Andreev, P., Benyoucef, M., & Hood, D. (2019). The role of lead management systems in inside sales performance. *Journal of Business Research, 102*, 163-177. doi:10.1016/j.jbusres.2019.05.018

Paschen, J., Wilson, M., & Ferreira, J. J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. *Business Horizons*.

Patterson, L. (2007). Marketing and sales alignment for improved effectiveness. *Journal of Digital Asset Management, 3*(4), 185-189. doi:10.1057/palgrave.dam.3650089

Quinlan, J. R. (1986). Induction of decision trees. *Machine learning, 1*(1), 81-106.

Raileanu, L. E., & Stoffel, K. (2004). Theoretical comparison between the gini index and information gain criteria. *Annals of Mathematics and Artificial Intelligence, 41*(1), 77-93.

Robnik-Šikonja, M., & Kononenko, I. (2008). Explaining classifications for individual instances. *IEEE Transactions on Knowledge and Data Engineering, 20*(5), 589-600.

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence, 1*(5), 206-215.

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), 1850-1856.

Rygielski, C., Wang, J.-C., & Yen, D. C. (2002). Data mining techniques for customer relationship management. *Technology in society, 24*(4), 483-502.

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.

Silge, J., & Robinson, D. (2017). *Text Mining with R*: O'Reilly Media.

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*, 564-579.

Štrumbelj, E., & Kononenko, I. (2014). Explaining prediction models and individual predictions with feature contributions. *Knowledge and Information Systems, 41*(3), 647-665.

Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management, 69*, 135-146. doi:10.1016/j.indmarman.2017.12.019

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*, 407-428. doi:http://dx.doi.org/10.1007/s11747-010-0211-8

Weiss, G. M. (2004). Mining with rarity: a unifying framework. *ACM SIGKDD Explorations Newsletter, 6*(1), 7-19.

Xu, X., Tang, L., & Rangan, V. (2017, 2017). *Hitting your number or not? A robust & intelligent sales forecast system*.

Sales pipeline Win propensity prediction: A regression approach, 854-857 (2015).

Yu, L., Wang, S., & Lai, K. K. (2006). An integrated data preparation scheme for neural network data analysis. *IEEE Transactions on Knowledge*

Data Engineering, 18(2), 217-230.

Zoltners, A. A., Sinha, P. K., & Lorimer, S. E. (2013). The Growing Power of Inside Sales. *Harvard Business Review*.

7. Chapter 7: Conclusion

The inside sales industry is growing fast and increasingly becoming global. Yet, little is known about the factors and practices that improve inside sales success. Accordingly, this thesis in form of five articles contributes to the inside-sales literature by identifying determinants of sales success and effective sales engagement strategies that can enhance sales success. The implications and contributions of the five articles in this thesis are summarized in Figure 7.1.

Figure 7.1 appears here

To identify the key determinants that facilitate the success of B2B inside sales and respond to calls for generalizations in sales and marketing research, Chapter 2 of this thesis reports on a comprehensive literature review and meta-analysis, identifying 31 B2B sales success determinants. We believe that the study is the first attempt to come up with a comprehensive sales success model that captures important determinants from all the key pillars of the selling process (i.e., salesperson, organization, customer and environment). The proposed model (see Figure 2.1) suggests that contemporary selling requires that a salesperson's competence and sales organization's operational and strategic practices must be aligned with the complex preferences and needs of customers. Moreover, the study conducted a moderator analysis and found that the influence of several determinants on sales success was significantly different in the inside sales context, thus providing some counter intuitive understanding of the situations under which several determinants can be more effective and sustainable for B2B inside sales success. This helps to achieve the first research objective and answers the first research question (i.e., "*What are the dimensions and determinants of inside sales success?")*.

To fill the knowledge gap on technology usage and effective lead engagement practices that can improve lead engagement outcomes in inside sales, Chapter 3 of this thesis introduces and empirically validates 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 determinants of inside sales performance, and the impact of the use of LMSs on these lead engagement drivers and enablers. Furthermore, using online survey data from 108 inside sales professionals, the study found that the use of LMSs 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. The findings of the study also revealed a negative relationship between call productivity (i.e., effort) and inside sales performance, and recommend the use of queue based LMSs for better inside sales performance.

Similarly, to further advance the body of knowledge on effective inside sales lead engagement practices, Chapter 4 uses a descriptive analytics approach to recommend to scholars and practitioners the best timeframes, number of calls, and best odds for first contact, along with more accurate insights on the number of contact attempts needed to engage with leads. In so doing, the study validates the role and significance of salesperson persistency, consistency, and speed of calls, and effective time management strategies that can improve lead engagement outcomes.

In Chapter 5, this thesis addresses an important but unresearched lead engagement aspect of inside sales by providing data-driven insights of what makes sales teams successful while engaging with leads. The study addresses this issue by conceptualizing and empirically validating the impact of Team composition and Team Dynamics (i.e., the nature of teams and how they interact with sales leads) predictors on B2B sales success. We believe that the study is the first of its kind to measure the impact of team selling engagement factors on inside sales success across various stages of the sales pipeline. The proposed models in the study will help managers understand important Team based lead engagement factors which they can use to effectively and efficiently coach and allocate salespeople to Teams.

Chapters 3, 4 and 5 second, provide a path to answering the second research question and help achieve the second research objective by identifying and validating key lead engagement factors for inside sales success.

Finally, in Chapter 6, this thesis develops several lead conversion models that integrate various lead engagement factors including salesperson effort (i.e., average number of calls, contact attempts per lead), salesperson performance, salesperson experience, call duration, days to lead, sales cycle time, call time, call day, company business model, industry and lead location. Our proposed models provide interpretable and explainable outcomes of patterns identified in the data across stages of the sales pipeline, thus tackling the limitations of widely used Black box models in the literature. The findings of the study affirm the importance salesperson performance, call duration, industry, salesperson effort, emails, days to lead and lead type for improving lead engagement outcomes during lead qualification and lead/opportunity management for B2B and B2C selling situations. This Chapter fulfills the third objective, and together with Chapters 3, 4 and 5 contributes to answering the second research question (i.e., *“How can data-driven analytics optimize lead engagement outcomes for inside sales?”*).

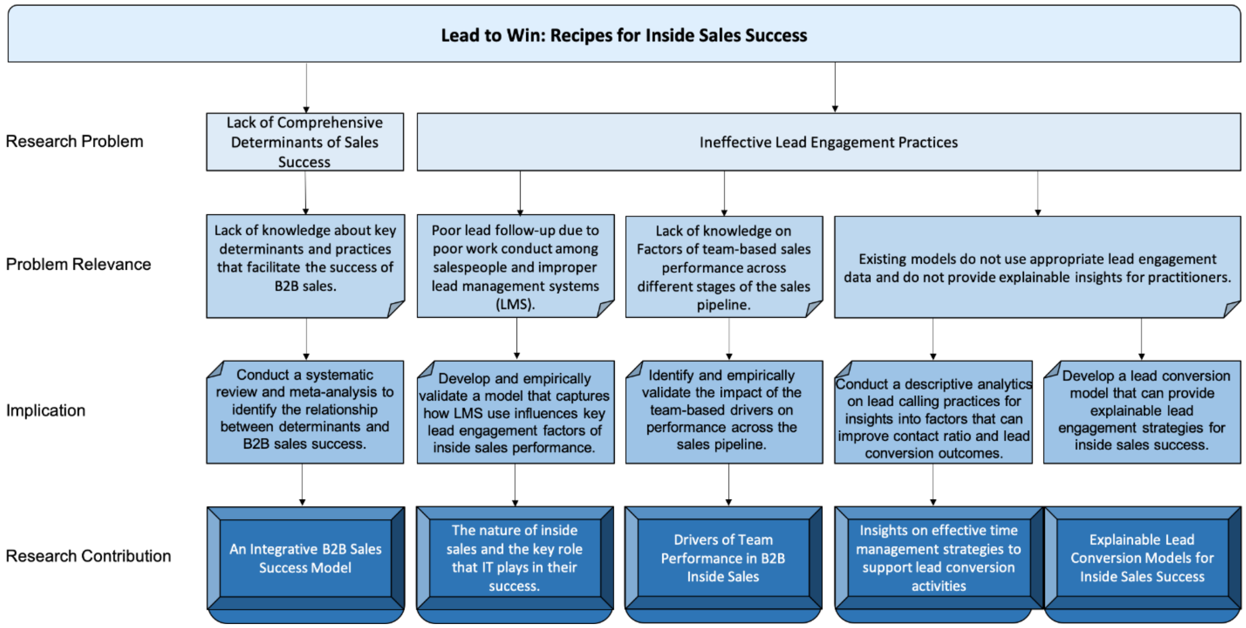

Figure 7.1: Overview of the Thesis by Articles

References

Bohanec, M., Bortnar, M. K., & Robnik-ikonja, M. (2017). Explaining machine learning models in sales predictions. *Expert jsystems with applications, 71*, 416--428.

Chapman, G. (2018). *Inside Sales vs. Outside Sales & The Evolving Art of Communication*.

Churchill Jr, G. A., Ford, N. M., Hartley, S. W., & Walker Jr, O. C. (1985). The Determinants of Salesperson Performance: A Meta-Analysis. *Journal of Marketing Research, 22*, 103-118.

Eitle, V., & Buxmann, P. (2019). *Business analytics for sales pipeline management in the software industry: a machine learning perspective.* Paper presented at the Proceedings of the 52nd Hawaii International Conference on System Sciences.

Gessner, G., & Scott Jr, R. A. (2009). Using Business Intelligence Tools to Help Manage Costs and Effectiveness of Business-to-Business Inside-Sales Programs. *Information Systems Management, 26*, 199.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213-236.

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.

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:* .

Järvinen, J., & Taiminen, H. (2016). Harnessing marketing automation for B2B content marketing. *Industrial Marketing Management, 54*, 164-175.

Ohiomah, A., Andreev, P., Benyoucef, M., & Hood, D. (2019). The role of lead management systems in inside sales performance. *Journal of Business Research, 102*, 163-177. doi:10.1016/j.jbusres.2019.05.018

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.

Ohiomah, A. 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.

Pullins, E. B., Timonen, H., Kaski, T., & Holopainen, M. (2017). An investigation of the theory practice gap in professional sales. *Journal of Marketing Theory Practice, 25*(1), 17-38.

Rapp, A., Beitelspacher, L. S., Schillewaert, N., & Baker, T. L. (2012). The differing effects of technology on inside vs. outside sales forces to facilitate enhanced customer orientation and interfunctional coordination. *Journal of Business Research, 65*, 929-936. doi:10.1016/j.jbusres.2011.05.005

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), 1850-1856.

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.

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. doi:10.1108/08858621011077763

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*, 564-579.

Thaichon, P., Surachartkumtonkun, J., Quach, S., Weaven, S., & Palmatier, R. W. (2018). Hybrid sales structures in the age of e-commerce. *Journal of Personal Selling and Sales Management*, 1-26.

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*, 407-428. doi:http://dx.doi.org/10.1007/s11747-010-0211-8

Yan, J., Gong, M., Sun, C., Huang, J., & Chu, S. M. (2015). *Sales pipeline win propensity prediction: a regression approach.* Paper presented at the 2015 IFIP/IEEE International Symposium on Integrated Network Management (IM).

Zoltners, A. A., Sinha, P. K., & Lorimer, S. E. (2013). The Growing Power of Inside Sales. *Harvard Business Review*.