The Drivers of Team-based Inside Sales Performance at Different Stages of The Sales Pipeline

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ABSTRACT

There is a lack of academic research on sales teams, despite team selling becoming more prominent in recent years. Particularly in Inside Sales, there is a lack of clarity as to what are the drivers of optimum team-based selling and their degree of effect on sales performance. We utilize a team-based approach that aims to study the characteristics of Inside Sales teams and their interactions with business leads, using data from a well-reputed leads management software vendor. Based on prior team-based constructs in the literature, we built a framework that posits Quality of Team Composition, Task Utility and Intra-team Coordination leading to different categories of sales performance at various stages of the sales pipeline via their reflective variables.

We tested our conceptual model in the following fashion: first, we used text mining on sales results to classify the different stages of the sales pipeline. Following that, we measured the conversion ratio at each stage as appropriate. Next, we discretized each conversion ratio into three levels of performance groups. The outcome variables in the model are different categories of team performance at each stage of the sales pipeline. Subsequently, we used multinomial logistic regression to regress our outcome variables on our team-based predictor variables in the hopes of establishing and validating important drivers for nuanced Inside Sales success.

We uncovered new insight regarding team-selling best practices, using pre-identified constructs from the literature which are uniquely suited to teams and also constructs which are aggregated at a team level from an individual level. Our study is especially relevant to the Inside Sales process, as the outcome measures relate to the sales pipeline. Our main finding was that in there is a difference in skills required at different stages of the sales pipeline, in that more customization and experience is needed at the more advanced stages, whereas more repetition of activity is needed at the beginner stages. We also found that smaller team sizes tend to do better in Inside Sales, which

was an unsettled research question in team research with plenty of evidence in favor of both smaller and bigger teams.

Additionally, even if it was not a primary goal of our study, by virtue of classifying the leads by their final outcomes, we stumbled across an interesting finding, which is that an overwhelming majority of the sales leads tend to stay at one stage in their entire lifecycle. The implications of all our findings are very relevant to both practitioners and researchers of Inside Sales who are interested in team-based sales optimization. More research should be done in the field of Industrial Marketing, building upon what we found to be true for the B2B sector.

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CHAPTER 1: INTRODUCTION

Team-based selling is a trending approach in sales with over 75% of companies using sales teams (Cummings, 2007). In their report on Human Capital Trends, Deloitte found that organizations are increasingly employing teams (Schwartz, Bohdal-Spiegelhoff, Gretczko, & Sloan, 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 selling) compared to underperformers (State of Sales, 2015). Hence, the virtues of team selling are widely appreciated for their ability to increase performance, which explains team selling's increased prominence in organizational design in recent years. However, there is a dearth of research on the factors that lead to the success of team selling (Perry, Pearce & Sims Jr., 1999).

Team-based selling has become an integral part of the sales strategy of organizations. The increasing number of stakeholders from the buyer's side as well as the increasing complexity of the selling tasks, have led to more organizations adopting selling teams instead of relying upon individual salespeople (Smith & Barclay, 1993). With greater strategic focus on relationship building with buyers over the decades, it is more difficult for one person to strictly sell and not be involved in any other value adding activities that help build a relationship (Cannon & Perreault, 1999). So the need for multi-skilled teams where people coordinate their resources has become imperative to manage ongoing sales relationships.

Adamson, Dickson and Toman (2014) write that the focus has shifted from individual performance to network performance in sales in organizations. Network performance is defined as how much people give to and take from their coworkers. They report that from 2002 to 2012, the impact of individuals' task performance on unit profitability decreased by 27% on average. At the

same time, the impact of employees' network performance increased by 27%. It is therefore understood that the best salespeople collaborate more with their colleagues for optimum performance. They rely upon each other to coordinate resources in the best way possible to deliver results. One of the key facilitators of such a transformation is sales technology. The use of sales information technology enables an easy transfer of knowledge, experience and skills, to strengthen network ties within companies.

The best example of such sales technology is salesforce automation (SFA) software, of which there are various kinds in the market. Morgan and Inks (2001) define SFA as the use of information and communication technologies to perform selling or sales management tasks. Such technologies come in the form of marketing automation software, customer relationship management (CRM) software, and lead management software (LMS), which manage sales leads. A sales lead is defined as a member from your target market who has signalled interest in your product (Carrol, 2006). Vendors of software such as LMS have inundated the sales and marketing departments across industries (Ahearne, Jones, Rapp & Mathieu, 2008). They have experienced tremendous uptake from Inside-Sales programs in companies that use such software to conduct their operations (Magnotta, 2018; Martin, 2013). Inside Sales are defined as organized sales that are conducted remotely or virtually usually from a central location, as opposed to an outside selling force which engages in more traditional face-to-face selling (Gessner & Scott, 2009; Rapp, Beitelspacher, Schillewaert, & Baker, 2012).

A greater number of stakeholders from the buyer's side, an increased complexity of the sales process and the use of sales information technology have necessitated the existence of sales teams in the modern era. Yet, academic research on team selling has not caught up to speed with practitioner research (Moon & Armstrong, 2013). While evaluating Team-based selling's

performance against individual selling is rare in the literature, Team-based Selling is declared more efficient in the limited occasions where the two types of selling have been directly contrasted (Steiner, 1976; Batt, 1999). Garrett and Gopalakrishna (2017) found that people performed better at team tasks than at individual tasks. This further magnifies the importance of team selling, not just as a practice in of itself, but as the better method of selling. Additionally, even if the two selling methods are not contrasted, team-based factors have a moderating effect on individual performance (Carboni & Ehrlich, 2013). Hence, its importance is underscored by the fact that it adds value at both the team level and individual level.

The term "team" has replaced "work group" to describe a collection of individuals seen as an entity in the workplace (Guzzo & Dickinson, 1996). The term team implies a greater sense of cohesiveness, interdependency and shared purpose than the term group (Katzenbach & Smith, 1993, Neuman & Wright, 2009; Baker & Salas, 1997). Modern sales has 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 job design is defined as when there are two or more people working in a group who are dependent on each other's activities and who share a common goal (Rajagopal & A.Rajagopal, 1998 ; Salas, Dickinson, Converse, & Tannenbaum, 1992).This is applicable to our case, as in Inside Sales, each team is assigned a particular set of leads or a particular project consisting of a certain kind of leads. The team members are expected to work together to accomplish a shared objective marked by the interdependency of their tasks. With the advent of technology, team members are more fluid than they have been in the past, in the sense that they can be in and out of multiple teams depending on the project (O'Leary, Mortensen & Woolley, 2011).

The following motivation section describes the situation and symptoms that culminated into the research question. Such a process is empirical in nature, as it looks to the industry to provide cues for research objectives instead of focusing on existing theories. Once the problem area is identified, we highlight the research question that this study attempts to answer.

1.1. MOTIVATION

As the world's business outlook has shifted from a transactional-based economy to a relationship-based economy, the concept of team selling has grown concurrently with the use of SFA. SFA's leverage as a tool has increased as a way to initiate and maintain relationships with sales prospects and customers alike. Currently in the US, the total Enterprise Software market is $49.1 billion, out of which CRM comprises a 29% segment (Industry at a Glance, 2018). Note that the terms SFA and CRM are used interchangeably (Ahearne et al, 2008; Avlonitis & Panagopoulos, 2009). The CRM industry is defined by IBIS World as software platforms for managing a company's interactions with customers, clients and sales prospects (Curran, 2017). Hence, lead management systems (LMS) is included in the domain of CRM.

The growth of the total Enterprise Software market over the past five years, and projected growth over the next 5 years are 6.6% and 3.2% respectively. However, for the CRM segment by itself, these numbers are 11.3% and 7.5% respectively (Industry at a Glance, 2018). Thus one can notice the rapid rise of SFA/CRM software, and its increasing stake in the Enterprise Software market. There was 16% growth per annum in the CRM/SFA industry before the credit crunch of 2008 (Payne, 2009). This growth would have been even more spectacular had it not been for the dotcom crash of the early 2000s. Nevertheless, the advent of SFA pushed through that crisis, as it did the 2008 global recession, and it continues to be a mainstay for businesses today.

Despite team-based selling becoming more prominent via the use of SFA systems such as LMS, there is discontent in the rate of return on investment for such sales technology. 55% to 75% of companies fail to meet their expected rate of return according to public data (Zablah, Bellenger & Johnston, 2004). 70% of all implemented SFA projects lead to losses or no bottom line improvements according to a Gartner report (Reimann, Schilke & Thomas, 2009). Thus we notice that while the concept of team selling and usage of SFA grows contemporaneously, there is a lot more expected of SFA in terms of delivery. Such a chasm between expectations and results can be explained by a large performance variance in team-selling via SFA usage, where different teams get different results albeit using the same tools.

We embarked on this research study with the primary intention of understanding what drove team-based Inside Sales performance. To narrow down our target population where we would measure the team-based constructs, we turn our focus to users of LMS software. As previously described, there is a great variance of performance in LMS usage by teams, which makes it an ideal substrate of population to conduct our study on. We focus on companies in the business-to-business (B2B) sector, in the Insurance and Marketing & Advertising industries. The B2B sector is known for its use of SFA software such as LMS. It is not that the business to consumer (B2C) sector does not use SFA software, only that they are more reliant on reaching the masses through advertising. They do not emphasize account based selling as much as much as the B2B sector does, where every sales lead is highly valuable (Kumar & Reinartz, 2012; Moore, Raymond & Hopkins, 2015). Hence, as our study aims to measure the performance of progression through the sales pipeline, it is more relevant to the B2B sector.

1.2. PROBLEM STATEMENT & RESEARCH QUESTION

We observe the lack of research done on the drivers of team-based selling success despite team-based selling's rising prevalence in the industry. There is a lack of understanding as to what constructs can be studied at a team level which would explain the variance of performance in Inside Sales. There is no mandate when it comes to identifying the best of these team-based constructs, the optimization of which would increase team-based sales performance. Moreover, there are no academic studies that measure performance based on leads pipeline progression, which is a process commonly used in Inside Sales and hence has great relevance to the Inside Sales process. Taking into account these current gaps of knowledge, we structure our research question as: ***What are the drivers of team-based Inside Sales performance pertaining to the leads pipeline in the B2B sector?***

1.3. RESEARCH OBJECTIVE

We list five objectives that will enable us to answer the research question posed prior. In chronological order, they are listed below.

1. **Formalize the performance of Inside Sales teams. This includes defining the sales lead pipeline, and its stages.**

   In order to formalize the performance of Inside Sales teams, we have the responsibility of choosing an objective outcome measure amongst the many that are available in the literature. Objectivity is important because it enables a fair comparison of teams within an organization, and between organizations. To this cause, we first want to define the various stages of the sales pipeline that are usually seen in Inside Sales, so the outcome measure is more nuanced and appropriate for Inside Sales. This gives us the ability to compare the

effect of team-based constructs on the performance of sales teams at various stages of the sales pipeline.

2. **Systematize existing knowledge regarding team-based factors that impact the performance of Inside Sales teams.**

   There is prior literature on the drivers of team-based success in sales. For the purpose of our study, we only focus on predictors that have to do with the characteristics of teams and their interaction with sales leads. This allows us to fixate on our research question as we are dealing with Inside Sales teams who use SFA systems such as LMS. Much like the outcome variable, we also want our predictor variables to be objective. Hence, we look for those team characteristics and sales lead interaction constructs that have direct measures or have appropriate proxies, which can be quantified directly from the field environment. We avoid those constructs which are subjective upon self-reporting or survey based measures. It should be noted that in addition to using papers to identify relevant team-based factors that fit our criteria, we also use studies on individual salespersons to further develop those constructs. This is because in some cases, team-based constructs are aggregations of individual-based constructs who are a part of that team.

3. **Classify stages of the sales pipeline and create relevant performance ratios and levels of performance, which shall serve as the outcome variables of the study.**

   First, we shall identify the stages of the sales pipeline from our data. Second, we shall discretize the performance at various stages of the sales pipeline into categorical outcome variables.

4. **Develop a conceptual model of Inside Sales team performance based on previously identified predictor and outcome variables from objectives 2 and 3 respectively.**

We will build a model to show the hypothesized relationships between each of the previously identified team-based constructs and sales performance at multiple stages of the sales pipeline. The direction of each hypothesized relationship will be determined by supporting literature.

5. **Empirically validate the proposed model.**

Finally, there is the task of empirically validating our proposed model for statistical significance, which also includes validating the direction and degree of effect of each pathway in which sales teams can achieve greater performance. We shall test our model by regressing our outcome variables on our predictor variables.

CHAPTER 2: BACKGROUND

The background chapter addresses the first two research objectives. We briefly describe the literature review process that was undertaken to meet the first two objectives from our Research Objectives section. We take a rationalist approach, and hence consider all relevant literature on the subject matter to gain an understanding of the extant theories. It is on shoulders of such literature that we later construct a new model for team-based success in Inside Sales, contingent upon the data that is available to us. After describing the literature review process, we delve into the remainder of the background section which covers key themes of the paper that are essential to understand. They consist of: the classification of stages in the sales pipeline, sales performance and the many predictors or team-based Inside Sales performance.

2.1. LITERATURE REVIEW

In order for us to answer our research question, a literature review was conducted on three main areas, namely: classification of stages of sales pipeline; types of team-based sales performance; and drivers of team-based sales performance. The first two areas correspond to objective one from the Research Objective, while the third corresponds to objective two. Our search strategy is best described as exploratory in nature where we aim to synthesize information by comprehensively searching each research area. Such a strategy best fits the definition of a scoping review where the goal to is to preliminarily assess the nature and range of a broad topic area (Arksey & O'Malley, 2007; Paré, Trudel, Jaana & Kitsiou, 2014). After synthesizing the contents of an explicit selection of papers, both narrative commentary and tables are used to present the information in line with Grant and Booth's (2009) instruction for conducting a scoping review.

The search terms and the electronic databases used are tabularized (Please refer to Appendix A), where the search terms are categorized into objectives one and two from the Research Objective section. The search terms were constructed using the Boolean operators AND and OR, to see if an article contained all the necessary information that was sought, and to see if they existed under various synonyms respectively. Quotation marks and asterisks were also used to extract specific concepts and consider all root variants respectively. Both business databases and interdisciplinary databases were used in the search.

All search results were ranked in terms of relevance. We read the title and abstract of each article to decide if it merited further inspection. We did this until the title and abstract stopped becoming relevant. The only two filters that were used were the "peer reviewed" and "English". Using any other filters posed a risk of unintentionally filtering out information that could be relevant to our study. After all suspected relevant articles were rounded up, we skimmed each article to more accurately assess if it would be constructive to our study. Such an approach can be more laborious on the front end, but it ensures that no relevant article is unintentionally omitted in the initial search.

Via the scoping review, we were firstly able to gather an understanding of all the research that has been done in the main and periphery areas concerning our research question. Such a dive into the literature enabled us to distinguish the important articles from the extraneous articles. We were then able to select and focus on only the necessary pieces of literature which addressed our research objectives.

2.2. CLASSIFICATION OF STAGES IN SALES PIPELINE

Published academic literature on the classification of stages of a business lead is very sparse, as opposed to gray literature, industry literature, and doctoral theses, where there is more material on this subject. Nonetheless, we focus on the available academic literature published in journals due to them undergoing higher scrutiny. Jolson and Wortuba (1992) lay out three main steps in the selling process, called suspecting, prospecting and qualifying. Suspecting refers to guessing the needs and buying intent of a particular sales lead. Prospecting refers to categorizing the sales leads as having the right needs and buying intent to be a potential customer. Qualifying is an advanced form of prospecting where the sales leads are further winnowed in terms of displaying the right actions or having the right characteristics, which are ideal for a future sale. Smith, Gopalakrishna and Chatterjee (2006) propose a three-stage model of the sales process. In order, the stages are lead generation, conversion of leads to sales appointments and conversion of appointments into sales. Jaramillo and Marshall (2004) have the same three steps, along with the prospecting stage between lead generation and appointments.

The sales funnel divides the customer acquisition process into multiple stages (Ang & Buttle, 2006; Patterson, 2007). D'Haen and Van Den Poel (2013) classify a sales funnel into four stages: suspects, prospects, leads and customers. We opt to substitute the word "lead" with "opportunity" or "appointment" as it is consistent with the aforementioned literature. This is because we are describing the journey of a lead, and hence "lead" cannot itself be the title of one of the stages of the sales pipeline. Henceforth, after juxtaposing various stages of a lead from different papers, we obtain a total of five identified stages of a lead as it moves along a sales pipeline. These are: Suspect, Prospect, Qualified, Opportunity and Client. Taking into account the definitions from prior papers where the differences between each step are clearly articulated, we define each step

in the following manner. A suspect is a new lead which has not been contacted yet. A prospect is a lead that has been contacted, but has not yet been qualified yet to see if it has the budget, authority, time and need for the product. The lead is qualified when an appropriate fit has been determined for the aforementioned requirements. A qualified lead becomes an opportunity when an appointment or further meeting is established with the decision maker where a final sales pitch occurs. If the lead agrees to buy, it becomes a client. These five stages can potentially be the different stages we refer to when measuring success at multiple stages of the sales pipeline.

Furthermore, sales leads can be classified as won, lost and 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 customer, 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 because of various reasons. A lead can be cancelled because of a loss of interest, an unsurmountable obstacle or a difference that hinders progression, or simply a loss of contact. The classification of "lost" at the final stage can be extended to the earlier stages as well to mean "cancelled". Thus every stage can have just two outcomes, "won" or "lost", where "won" means progress and "lost" means cessation of progress. Therefore, 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.

2.3. OUTCOME: SALES PERFORMANCE IN THE SALES PIPELINE

Team-based sales performance is an under researched area in the realm of Inside Sales performance (Smith & Barclay, 1993; Perry et. al, 2009). Team-based performance is defined in terms of behavior and outcome (Beal, Cohen, Burke & McLendon, 2003; Cohen & Bailey, 1997; Schwepker Jr. & Good, 2011). Behavior refers to those actions, abilities and tendencies that supposedly lead to a higher success rate. Behavior can be assessed, although subjectively.

Outcome refers to actual countable sales results that indicate performance, such as market share, volume of sales, new accounts and profits. Outcome can be assessed objectively.

As this study relies on the sales pipeline, we use quantifiable sales conversions as a measure at each stage of the sales pipeline. Several papers suggested such an output measure for sales performance because of its objectivity (Ahearne, Srinivasan & Weinstein, 2004; Smith & Barclay, 1993). Being a quantitative measure, there is no room for qualitative observer dependent interpretation. Thus, sales teams will be assessed based on the same quantifiable output. Furthermore, a sales conversion (or any advancement leading up to a sales conversion) is more a measure of effectiveness and less a measure of efficiency. Effectiveness is a more objective measure of sales performance than efficiency, because while efficiency informs us about the ability of the sales team to accomplish a desired outcome, effectiveness informs us about the actual accomplishment of a desired outcome.

In a study with 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, Pullins & Mallin, 2009). The former is a sales outcome measure, while the latter is a sales activity measure. Both are highly objective as they are dependent on the successful acquisition of a customer. We intend to use both in this research. First, the total number of successful conversions from stage to stage will be counted, and second, the success ratio of each stage will be calculated by dividing the total number of successful conversions to the next stage by the total number of available leads at the current stage.

Smith and Barclay (1993) used sales targets as a performance output in their study where closing a business deal was the idea of the sales target objective. Our study uses the same definition (i.e. successfully converting a sales lead) albeit in the framework of a sales lead pipeline where there

are multiple conversions before a lead becomes a customer. Analyzing the sales pipeline is essential for business success, and estimating the conversion of opportunities is said to be the "fundamental block" for sales management (Yan, Gong, Sun, Huang & Chu, 2015). Hence, we chose sales performance vis-à-vis sales conversion at each stage of the sales pipeline as our outcome variable.

2.4. PREDICTORS

The predictors of team-based sales performance are diverse and plentiful. But as this is a study on team-based performance in Inside Sales, the search criteria is limited to the characteristics of the teams, and their interactions with LMS. Furthermore, because the outcome of the study is defined so stringently as actual quantifiable conversions of sales leads, the same objective rigor is applied to the 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 also at the team level such as team potency, team cohesiveness and team identification.

From our scoping review, we identified the following three main research areas in the prediction of team-based Inside Sales performance which can be objectively measured: composition of the selling team which includes team design; task utility which consists of the interactions of sales team members with the LMS; and intra-team coordination which consists of joint interactions of the sales team members with the LMS. The existing literature related to each of these three areas is reviewed in the following sections. It is also tabularized in Table 1.

The latent constructs are described first, followed by the reflective variables that are indicative of them. For the purpose of this study, we are not measuring the latent constructs. Nevertheless,

we describe them to better appreciate the foundation of our measured variables. This allows us to better summarize the key team-based constructs via their parent groups.

Table 1

Note: This table covers the literature used to identify our team-based constructs affecting performance. There were other studies done at solely an individual salesperson level, covering some of these same variables. We refer to these studies throughout this document in order to further develop our understanding of the relevant variables.

Targeted Categories of Team-based Predictors of Performance from our Objectives			Team Characteristics			Interaction with Sales Leads				
Identified Subcategories			Design	Composition		Task Utility		Intra-team Coordination		
Variables in our Study			Team Size	Team Experience	Team Effort	Task Input	Team Goal Monitoring	Specificity of Role	Repetition	Intra-team Communication
Paper Title	Authors	Relevant Pathways								
Empowered selling teams: How shared leadership can contribute to selling team outcomes	Perry, Pearce & Sims Jr. (1999)	Team Size → Shared Leadership (Moderator) → Internal Role Performance Maturity → Shared Leadership (Moderator) → Internal Role Performance Effort→ Sales Performance Task Characteristic (interdependence) → Sales Performance	✓	✓	✓			✓	✓	
A Meta-Analytic Review of Relationships Between Team Design Features and Team Performance	Gooding and Wagner (1985)	Team Size → Performance	✓							
Relations between work group characteristics and effectiveness: implications for designing effective work groups.	Campion, Medsker and Higgs (1993)	Relative Size→ Productivity Task Interdependence→ Productivity Communication within groups→ Productivity	✓					✓	✓	✓
Team Dimensions: Their Identity, Their Measurement and Their Relationships	Nieva, Fleishman and Reick (1985)	Group Size→ Performance	✓							

Work Groups and Teams in Organizations	Kozlowski and Bell (2001)	Team Size→ Success	✓						
Team-based employee involvement programs: effects of design and administration	Magjuka and Baldwin (1991)	Team Size→ Team Effectiveness	✓						
Managing sales teams in a virtual environment	A.Rapp, Ahearne, Mathieu and T. Rapp (2010)	Team Experience→ Performance		✓					
Technology Usage and Sales Teams: A Multilevel Analysis of the Antecedents of Usage	Weinstein and Mullins (2012)	Team Sales Experience → Technology Usage Team Goal Acceptance → Technology Usage *Tech usage is said to lead to performance in other studies		✓			✓		
Making sales technology effective	Hunter and Perreault Jr. (2007)	Experience→ Administrative Performance Effort→ Administrative Performance Communicating→ Administrative Performance		✓	✓				✓
Key accounts and team selling: a review, framework, and research agenda	Jones, Dixon, Chonko & Cannon(2005)	Team Tenure → Relational Learning Outcome→ Firm Outcome		✓					
Does experience matter? The effect of founding team experience on the survival and sales of newly founded ventures	Delmar and Shane (2006)	Founding Team Experience → Sales		✓					
Intangible sales team resources: Investing in team social capital and transactive memory for market-driven behaviors, norms and performance	Bachrach, A. Rapp and Mullins (2016)	Learning Effort → Selling Performance Team Goal Monitoring → Learning Effort → Selling Performance Transactive Memory Systems → (Moderator) Selling Performance		✓			✓		
Task-performing Groups	Steiner (1976)	Task Input→ Goals				✓			
Team effectiveness: beyond skills and cognitive ability.	Neuman and Wright (2009)	Checking & Form Completion → Task Performance				✓			
Composition, process, and performance in self-managed groups: The role of personality.	Barry and Stewart (1997)	Task Input→ Impact				✓			
Organizational Behavior: Group Structure, Process, and Effectiveness	Gist, Locke & Taylor(1987)	Task Characteristic→ (moderator)Group Performance				✓			

The role of team goal monitoring in the curvilinear relationship between team efficacy and team performance.	T. Rapp, Bachrach, A. Rapp & Mullins (2014)	Team Goal Acceptance → (Moderator) Team Performance					✓			
Teams in organizations: Recent research on performance and effectiveness	Guzzo and Dickinson (1996)	Group Goals→ Team Effectiveness					✓			
Team Selling Effectiveness:: A Small Group Perspective	Smith and Barclay (1993)	Member Interdependence →Perceived Task Performance						✓	✓	
Group Effectiveness: What Really Matters?	Shea and Guzzo (1987)	Task Interdependence → Group Task Effectiveness						✓	✓	
A Meta-Analysis of Cohesion and Performance: Effects of Level of Analysis and Task Interdependence	Gully, Devine & Whitney (1995)	Task Interdependence →(Moderator) Performance						✓	✓	
A Meta-Analytic Review of Relationships Between Team Design Features and Team Performance	Stewart (2006)	Intra-team Cooperation → Performance						✓	✓	
Team performance and control process in sales organizations	Rajagopal & A. Rajagopal (1998)	Team Coordination→ Sales unit Performance						✓	✓	
Sales teamwork: a dominant strategy for improving salesforce effectiveness	El Ansary, Zabriskie and Browning (1993)	Temam work(coordination) → Salesforce Effectivenss						✓	✓	
Team Structure and Performance: Assessing the Mediating Role of Intrateam Process and the Moderating Role of Task Type	Stewart & Barrick (2000)	Interdependence(task interdependence)→ Work Team Performance Interdependence(Communication)→ Work Team Performance						✓	✓	✓
Key account teams: success factors for implementing strategy	Lai and Gelb (2015)	Within team communication → Sales Result								✓

2.4.1. QUALITY OF TEAM COMPOSITION

The terms *team* and *group* are used interchangeably. Group refers to the contribution of each individual member in a team in terms of skills, abilities and disposition (Hollenbeck, Ilgen, LePine, Colquitt & Hedlund, 1998; Tesluk & Mathieu, 1999). Team composition is a latent construct in the scope of our study, which is formed by three observed variables: Team size, Team experience and Team effort. Experience is seen as possessing greater skills and abilities. A salesperson's skills and abilities are expected to grow with the duration of time he/he spends on a certain sales lead or use a LMS. Effort can be looked upon as a type of disposition that each salesperson has towards work, in terms of the level of activity. As for size, it is a basic element of team design which determines the number of members there should be per team. Despite it being a design feature, Kozlowski and Bell (2001) and Smith and Barclay (1993) include team size under team composition. It is important in terms of its aggregative properties in the sense that more effort and experience would be equal to a better performing team if one uses aggregate measures to define the team variables of experience and effort. Hence team size, along with team effort and team experience are important components of a favorable team composition.

2.4.1.1. TEAM SIZE

In order to define team size, we must first define a team. As stated before, team-based job design is defined as when there are two or more people working in a group who are dependent on each other's activities and who share a common goal (Rajagopal & A. Rajagopal, 1998; Salas et al., 1992). So naturally, the number of people in the context of such a team design forms the team size. Each team is assigned a particular set of leads or a particular project which receives a certain type of leads. Both scenarios are defined by their temporal nature. Indeed, 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.

2.4.1.2 TEAM EXPERIENCE

Weinstein and Mullins (2012) define team experience as the aggregation of each salesperson's experience in a team, where experience is the length of service over the whole career of each team member. Mintu-Wimsatt and Gassenheimer (2000) and A.Rapp, Ahearne, Mathieu and T. Rapp (2010) constrain the boundaries of such a definition of a team to mean length of service in the current position of each member of the team. The latter definition is adopted for our study because we do not have, in our data, records of the salesperson's experience outside the context of their current organization.

In general, there are two ways of measuring team experience. One is by aggregating the team experience of each member, the other is by measuring the heterogeneity of experience within a team, where a greater heterogeneity is seen as a positive trait. In this study, the aggregate experience of all members in a team is used since several studies used such an aggregation technique (Weinstein & Mullins, 2012; T. Rapp, Bachrach, A. Rapp & Mullins, 2014).

2.4.1.3. TEAM EFFORT

To the best of our knowledge, team effort has not been defined in prior literature, but individual salesperson's effort is defined as the force, energy or activity with which work related tasks are accomplished (Brown & Peterson, 1994). Hence we aggregate the effort of each team member to mean team effort. Effort is also described as the persistency of salespeople in terms of length of time committed to work despite failure (Sujan, Weitz & Kumar, 1994). Therefore it reveals the force or energy of teams with which they carry out work related tasks, such as calling sales leads.

In this case, length of time translates to the number of call attempts, where the sales team persists with its activity of calling sales leads despite failure.

2.4.2. TASK UTILITY

Levine & Moreland (1990) state the potential importance of team task and inter member communication for measuring team productivity. Collectively, this can be described as the latent construct of task utility, where team task includes the observed variables of Task input, while Inter-member communication refers to the observed variable of team goal monitoring.

Job analysis involves tracking job components which determine job performance (Neuman & Wright, 2009). Hence in order to measure performance, it is important to measure the interactions of the sales teams with the LMS employed by the company, as it is a component of their job. Since using LMSs is a part of their job description, it is important to understand how efficiently they use it. Neuman and Wright (2009) identify forms completed, and checking as two subset measures for assessing job specific skills. Forms completed corresponds to task input, as it is being checked if a particular task has been inputted or completed. Checking corresponds to the quality of Task input, as is done to observe the accuracy or quality of the task that is completed. Jelinek, Ahearne, Matheieu and Schillewaert (2006) measure sales technology adoption by how frequently a salesperson uses the technology, and to what extent he/she fully utilizes the capabilities of that technology. These correspond to task input and the quality of task input respectively.

Barry and Stewart (1997) include measures called “pulls weight” and “quality concerns” to quantify the effect of task on group impact. “Pulls weight” is comparable to “form completion” as a salesperson is mandated to do his/her part. “Quality concerns” is comparable to “checking” as

one is expected to do his/her part with proper rigor and efficiency. Thus, Task input and the quality of task input repeatedly prove themselves to be important indicators of task utility.

2.4.2.1. TASK INPUT

Task input is defined by Barry and Stewart (1997) as fulfilling any responsibility towards achieving a certain goal. Researchers on teams have expounded task input and socioemotional input as moderators of team performance. While measuring socioemotional input is beyond the scope of this study, it is possible to measure the task input which leads to sales performance in the usage of LMS.

The task product must be specified before certain information cues can be recognized as task input (Wood, 1986). In our case, the task product is the set of attributes that make up the functionalities of the LMS. There are many information fields in such a system which act as opportunities of task input. The other part of Task Input is task characteristic, which is defined as the 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 inspects how well or thoroughly a task has been done.

2.4.2.2. TEAM GOAL MONITORING

Bachrach, Mullins and Rapp (2016) define Team goal monitoring as the facilitation of auxiliary corroboration to ensure that "critical market focused processes are activated and performance criteria are met" (p.9). Marks, Mathieu & Zaccaro (2001) concur that Team goal monitoring is a process by which the members of a team track progress towards the accomplishment of goals. This is applicable to our case as there is communication among team members pertaining to the mutual overseeing of progress.

There is a link between interpersonal cooperation and Team goal monitoring in that effective information sharing among members is only possible when team members are cooperative. Yilmaz & Hunt (2001) describe cooperation to be the sharing of skills, knowledge, time and effort with coworkers to achieve common objectives. Thus just like team goal monitoring, cooperation also contains a theme of sharing information to keep every member of the team on the same page for furthering a certain objective. Hence, it strengthens our case for measuring team goal monitoring via communication within teams where progress related information is shared.

2.4.3. INTRA-TEAM COORDINATION

The latent Intra-team coordination construct is formed by the observed variables Specificity of Role, Repetition and Intra-team communication. According to Stewart (2006), intra-team coordination captures task coordination activities within a team, rather than between a team and the rest of the organization. Such intra-team coordination fosters a type of interdependence where the team members depend on each other for information and knowledge (Campion, Medsker & Higgs, 1993). Therefore, team members have to be more specialized in order to become a better functioning and more coordinated unit. Such specialization is incumbent on having multiple roles in one team where that role is performed by only one person. So, high coordination is contingent on the existence of multiple specialized roles. High coordination is said to result in shared expectations and common behavior (Stewart & Barrick, 2000). This leads to repetitive behavior within a team where everyone is accustomed to executing a task in a certain way. High coordination is also said to open communication channels (Stewart, 2006). Team members have to effectively communicate with each other to achieve shared objectives.

Cespedes (1992) laments the lack of research on coordination within sales teams. He identifies two types of coordination, namely: coordination via planning and coordination via feedback. The

first of these corresponds to Specificity of Role and Repetition, the second corresponds to communication. Each indicator is further explained in the following passages. (See Section 2.4.3.1, 2.4.3.2 and 2.4.3.3)

2.4.3.1. SPECIFICITY OF ROLE

We define specificity of role as the number of specialized roles in a team, where one member is solely responsible for performing that one specialized role. It is a strong antecedent to task interdependence, which is defined as the extent to which salespersons 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 and members depend on each other. The workload is amply distributed in such teams. One of the measures for task distribution is workload distribution amongst salespeople (Rajagopal & A. Rajagopal, 1998), where each person is said to be specialized in a certain task. This again coincides with our idea of greater specificity to mean greater specialization.

2.4.3.2. REPETITION

The concept of repetition is close to a transactive memory system. Bachrach et al. (2016) propose 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 in a certain way. Hence, we define repetition as the iteration of sets by team members, where each set is a unique ordering of team members, each responsible for one or more roles. Lewis (2003) uses the measures of 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.

2.4.3.3. 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 and A. Rajagopal (1998) measure team coordination as communication and flow of directives with salespeople. While Levine and Moreland (1990) find little evidence for within-team communication leading directly to productivity, they do find it to have a positive impact on cooperation amongst team members. They attest to more equal participation because of electronic communication. Thus, intra-team communication is also a vital piece 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 irrespective of geographical barriers are able to better collaborate in order to accomplish relevant tasks and goals (Griffith & Dunham, 2015).

CHAPTER 3: METHODOLOGY

Hitherto, our first two research objectives are complete. We formalized the team-based performance in Inside Sales, and systemized the team-based factors that affect Inside Sales performance to identify the predictor variables that are relevant to us. Going forward, this chapter discusses the research design, the sample, and the operationalization of our predictor variables. Then we dive into the methodologies used to extract our outcome variables, build our conceptual model, and finally empirically test our model.

3.1. RESEARCH DESIGN

Our study explores the effects of the drivers of team-based Inside Sales on sales performance. For that we use quantitative methods on secondary data from our industrial partner, a major North American Lead Management Software Company. The quantitative approach is suitable for the type of applied research that we do, as it involves a large quantity of data that is already available and upon which predictive analytics may be performed.

3.1.1. DATA COLLECTION

Our study is data centric. Ensuring the maintenance and protection of the secondary data is important. Therefore, the data is stored in one computer located in a research lab at the University of Ottawa. This is done in order to geographically restrict its access to one place. It is stored in the computer's drive and not the cloud, as a security measure. The computer has the necessary anti-virus systems and firewalls to ensure the safety of the data while it is being processed. Furthermore, the designated computer is password protected, which adds another layer of security to the already locked lab doors. Such measures are necessary to protect the privacy of the data that our industrial partner entrusts us with.

3.1.2. DATA TRANSFORMATION

The secondary data we obtained from our industrial partner was very unorganized, so a lengthy process was followed to organize it according to the needs of our project. The assessment and preparation of the data involved filtering it to extract only the variables that are relevant for the scope of the research. Then it involved preparing or converting that data to correct units of measurement for subsequent analysis. The ultimate goal was to create a data file containing all the relevant variables which are ready to be analyzed.

3.2. SAMPLE

The sample needed for this study consists of B2B companies employing teams which have implemented lead management software in their Inside Sales operations. Six of these companies represent our sample, three from the insurance industry and three from the Marketing & Advertising Industry. The unit of analysis is the characteristics of each team derived from the team design or composition, or the interaction of team members with sales leads.

There are no issues in obtaining a minimum number of leads from these companies for the research to be statistically significant because it is common for companies to generate hundreds of leads each month. These leads in turn have hundreds of interactions everyday with the sales teams of the companies in question. While our unit of analysis is teams represented by the 4237 cases, the variables for those teams were derived from over three million interactions of sales teams with sales leads. Regarding the final number of cases after the raw data was converted to variables, Schwab (2002) states that there must be a minimum of ten cases per variable in multinomial logistic regression, which is the method used in Phase 3 of our research. We have nine predictor

variables, including industry. Considering our lowest amount of cases in Qualification Ratio, which is 1762 teams, we are still covered by that estimate.

This study will use nonprobability sampling. We make use of all the data that we have at our disposal from the six companies since the provider of this data is a lead management software company whose clientele represents our target population. The thought of doing quota sampling was also considered in order to have an equal representation of the different industries that these companies represent. But since this was a study were the raw data comprised of over three million interactions of sales teams with leads, the research would be better off with as much information as possible. Attempting to make a large volume of data manageable by taking smaller sample sizes overrides the scale of the data that makes it so appealing in the first place (Tinati, Halford, Carr & Pope, 2014). Narrowing the scope of interpretability by choosing only two industries helps with the external validity of the study.

3.3. MEASURES: PREDICTOR VARIABLES

3.3.1. TEAM SIZE

To measure Team Size, we count the average number of salespeople assigned to each sales team for all the leads that team has worked on. We do this by counting how many distinct IDs are within each ContactOwnerGroupID for every interaction history with a lead, then finding the average of this number for all the leads the team has worked on. ContactOwnerGroupID refers to the sales team that a lead is assigned to. Its IDs include the following: AddUserID, which is the ID of the salesperson who added the lead to the list; UpdateUserID, which is the ID of the salesperson who last updated the call data of the lead; and UserID, which is the ID of the salesperson who called the lead. Hence, by counting distinct IDs from these three variables per ContactOwnerGroupID

for each lead, we are able to ascertain the number of members in that sales team for that lead. To arrive at the team size, we can find the average of this number for every lead the team has worked on.

Team Size was a relatively straightforward measure to operationalize. Stewart (2006) and Gooding and Wagner (1985) both conducted a meta-analysis of studies that measured the effect of team size on performance. In all instances, team size was calculated by the number of members that were designated in teams. Those teams follow the prior definition of a team as established in the Outcome: sales performance in the sales pipeline section (see Section 2.3). The ContactOwnerGroupID constitutes such a team, as it is a group of more than one person, in charge of selling to leads, whose tasks are interdependent on each other.

3.3.2. TEAM EXPERIENCE

To measure Team Experience, we sum up the number of months a salesperson has been working in the organization for all team members. We first see when that salesperson's user account was created. Then we look at the date of the last contact made with a lead by checking the Call Date of the last CallHistoryID for that particular salesperson within that team. The difference between the user account creation and the latest activity determines the experience of that salesperson within his or her team. Following that, we sum up the experience of each team member to calculate the total experience for that team.

Measuring team experience by accounting for the duration of each team member's stay in the organization has been practiced before (A. Rapp et al., 2010; Mintu-Wimsatt & Gassenheimer 2000). It is different from measuring experience in the context of a singular team because team members can be members of multiple teams throughout their stint in the organization. Indeed,

greater team experiences have meant the presence of members in the team who were part of multiple teams prior (Rentsch, Heffner & Duffy, 1994).

3.3.3. TEAM EFFORT

To measure Team Effort, we count the average number of successful and unsuccessful contact attempts made by a particular ContactOwnerGroupID per lead. We do this by summing the total CallHistoryIDs for each ContactOwnerGroupID. CallHistoryID is a unique identifier for each call made. Thus, by summing the number of CallHistoryIDs for each ContactOwnerGroupID per lead, we can ascertain how many times that team tried to, or successfully established contact with that lead. By averaging this number for every lead the team has worked on, we arrive at team effort.

Many researchers have operationalized effort by counting the number of calls made by each salesperson (Brown & Peterson, 1994; Sujan et al., 1994). Such individual effort of team members may be aggregated to account for team effort. Calling is one of the features of an LMS. It is an actual activity that is recorded and requires effort; it is not merely an administrative task (Ahearne et al., 2004).

3.3.4. TASK INPUT

To measure Task Input, we count the average number of content words per call history comments made for each lead worked on by a team. Content words are nouns, verbs, adjectives and adverbs in a sentence. The comments variable in call history is a textual form of data. It is an observation made by the salesperson about the call he/she made. Adding the total number of content words of all call history comments for each lead gives us the total task input for that lead. Subsequently we can average this number for all leads worked on by a team to ascertain the task input of that team.

From a sales point of view, the input of data by salespeople is essential to understand the selling or buying situation (Tanner et al., 2005). Hence, fulfilling such responsibilities by salespeople is an important act which can and should be measured. Task Input has been measured by the survey measure of "pulls weight" which asks if the team members have done their part in contributing to the overall work process, and "quality concerns" which asks if a task has been done diligently (Barry & Stewart, 1997). In other words, it measures if salespeople have fulfilled the task they are responsible for with due diligence. Wood (1986) describes task input as a required act. It has also been measured by the survey item describing frequency of use and extent of utilization by Jelinek et al. (2006). Similar to our measure, task input has previously been measured by other researchers as the fulfillment of required duties with a particular level of meticulousness. More specifically, Ahearne et al. (2008) include "note taking" as a part of their archival IT use measures, which is what we are measuring.

3.3.5. TEAM GOAL MONITORING

To measure Team Goal Monitoring, we count the average number of LeadStatus updates for all leads worked on by a team. In other words, we count the number of different lead statuses for each lead, then average that number for all leads to obtain the team goal monitoring rating for that team. LeadStatus is a textual field like call history comments. It is the name and description of the status or position of a lead in its journey through the sales pipeline.

Marks et al. (2001) and Bachrach et al. (2016) use measures such as tracking progress towards a goal and monitoring the advancement towards a goal to measure team goal monitoring, which is similar to how we do it.

3.3.6. SPECIFICITY OF ROLE

To measure Specificity of Role, we count the number of user IDs in a team that serve only one role in the team's interaction with a lead. Subsequently, we average this figure for all the leads that team has worked on to ascertain the specificity of role for the team. Different roles in this case constitute AddUserID, UserID and UpdateUserID. All have been already defined in the team size subsection. While team size is calculated by counting the average number of distinct user IDs per lead for a team, Specificity of Role sees how many of these distinct user IDs perform only one role, as opposed to performing more than one role out of the three possible roles.

Campion et al. (1993) and Yilmaz and Hunt (2001) have both used measures of task interdependence to measure coordination within teams, which is dependent on everyone doing their part or being involved. Survey items measure the dyadic relationship between employees and their coworkers, regarding their ability to do their jobs well without information and assistance from each other. Other researchers measure team usage across all members of a team to verify if the SFA is utilized by all, hence reinforcing the notion of everyone being involved (Eggert & Serdaroglu, 2011; Schillewaert, Ahearne, Frambach & Moenaert, 2005).

3.3.7. REPETITION

To measure Repetition, 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. All have been already defined in the team size subsection. Combination of role refers to team structure, where each team member can be responsible for one or more role. We find all such combinations of roles in a team, each of which

constitutes an unique set. We then sum the number of times all sets are repeated per lead, and average the number for all leads worked on by a team.

Lewis (2003) and Barachrach et al. (2016) used survey measures such as lack of misunderstanding, working well together, and fulfillment of work promises to measure coordination and team goal monitoring. This suggests the perpetual continuity of work in what can be described as repetition. Along with involvement of differentiated roles, repetition of those roles is the other half of specialization. Lewis (2003) measured specialization with the survey items that measure the existence of different roles for different members of the team, and the necessity for each team member to be expert in his/her respective role. This demonstrates the need for repetition, where one repeats the given role until expertise is achieved.

3.3.8. INTRA-TEAM COMMUNICATION

To measure Intra-team communication, we sum the product of the number of content words in call history comments and lead statuses per lead, and the number of distinct members of the team responsible for inputting those call history comments and lead statuses. To arrive at intra-team communication, we count the average of this figure for all leads worked on by the team.

Counting the number of content words accounts for decisional and affective information exchanged between team members. Counting the number of different team members making the comments and updates shows the level of engagement in the team with regards to communication. Together, their product indicates how much intra-team communication is going on by taking into account both the participation and the quality of the participation. While intra-team communication has not been directly measured in the past, Rodriguez and Honeycutt Jr. (2011) measured collaboration as the willingness to communicate client needs. In order to do this, they attempted

to note all signs of communication flow between team members. Other researchers employed collaboration measures such as directive language pertaining to feedback and any information regarding the business, such as product attributes, competitors and customers (Rajagopal & A. Rajagopal, 2008; Yilmaz & Hunt, 2001). Note that it is intra-team communication that is being measured, but under the guise of collaboration.

3.4. IDENTIFYING THE OUTCOME VARIABLE MEASURES

This section corresponds to objective three from our Research Objective section, where we first identify the stages of the sales pipeline to calculate then performance ratios, and then discretize them into tiers to unearth our outcome variables. Distinct stages have previously been identified in the literature regarding the progress or journey of a business lead through the sales funnel or pipeline. The words funnel and pipeline are used interchangeably. It was our intention to confirm these stages of the sales pipeline via the extant taxonomy, but also propose a new taxonomy to describe new stages of the sales funnel if need be. Identifying and labeling different stages of the sales pipeline allows us to measure the variance in sales performance at those stages. We did this via topic categorization, which involves identifying the main theme in a text by employing both semantic and relational algorithms (Fan, Wallace, Rich & Zhang, 2006). This usually involves working with a number of predefined concepts.

3.4.1. PRELIMINARY FINDING: DETERMINING THE CONCEPTS

In our preliminary textual exploration of the data, we identified five distinct stages of the sales pipeline, four of which are documented in the literature, namely: Suspect, Prospect, Qualified and Client, and one new stage which we have chosen to label as “No Contact”. The chronological order

of these stages in the sales pipeline is as follows: No Contact, Suspect, Qualified, Prospect, and Client.

In order to derive the five stages from the data, exploratory text categorization was conducted using the software Leximancer, which uses a mix of semantic and relational algorithms to create concept maps. Leximancer was chosen because it is a concept or topic extraction tool (Smith, 2003). Leximancer creates concepts as indicated by grey dots. The more connected these concepts are to other concepts, the larger the size of that concept's grey dot. For a certain range of connectivity, Leximancer assigns a theme to a group of concepts, labelling the theme as the most connected concept in that theme. The size of the thematic circles bear no relevance, but the thematic circles are color coded from hot to cold in terms of the number of concepts present in the circle.

When salespeople report on (i.e., document) the results of their dealings with leads, the language they use can be very polysemous in the sense that one word can have multiple meanings. This is true for our data. Hence, it was important to choose concept extraction and not clustering for identifying themes of information, which we could then use to delineate the five stages of the sales pipeline. Whereas clustering separates concepts on the basis of mutual exclusivity, concept extraction separates concepts based on whether they share a common source word. We chose Leximancer as an initial exploration tool because of its ability to generate concept maps using its semantic and relational algorithms. Leximancer is recognized as an advanced tool for generating concepts and its use is validated by many studies (Nunez-Mir, Iannone, Pijanowski, Kong & Fei, 2016; Smith & Humphreys, 2006).

The stages of the sales pipeline were classified using text mining on the Result Codes sheet, which consist of codes for different Result IDs. A Result ID uniquely identifies different outcomes

of each call made to the lead. Sales teams from companies work on projects which receive sales leads. Each Project ID has different Result IDs which correspond to different Result Codes, as indicated by the Result Codes sheet. In total, there are 595,027 Result Codes used by teams. It was our intention to textually explore all the Result Codes to understand how sales teams classify the results of each call. This allows us to understand the different states of a lead as it progresses through the sales pipeline.

We are more interested in the concepts than the themes. This is because the result codes are all a sentence each, with no more than a few words on average. So semantically speaking, it is easy for group them with other result codes under one theme even if they represent different stages of the sales pipeline. It is quite likely that multiple concepts exist within one theme where the theme would not be an accurate descriptor of the stage. Hence, we examined all the concepts from the concept map (as produced through Leximancer) and noticed that they can be categorized under five stages of the sales pipeline, namely No Contact, Suspect, Prospect, Qualified and Client. There are many concepts which are too vague to be interpreted, but five types of concepts can be noticed from the concept map (see Appendix B). These concepts are binned into their categories in Table 2.

Table 2

Result Codes: Identification of the Stages from Leximancer

No Contact	Suspect	Prospect	Qualified	Client
• Wrong Number • Bad number • Left voicemail • Retry in n days • Call back	• Bad fit • Currently using " " • Wrong Person • Not interested	• Requested information • Requested call back • Scheduled • Dm-decision maker • Interested in future • Wants info • Refer	• Scheduled Appointment • Scheduled Meeting • Confirmed • Survey completed • Registered	• Client • Sold Account • Order completed

We were interested in uncovering many concepts, then seeing if those concepts converge around certain themes that we have identified from the literature, or completely new themes. If we set a predefined number of concepts to begin with, a lot of information could be lost as each concept could have multiple important sub concepts. Thus, the strategy is to first uncover as many concepts as possible, so each topic is representative of a singular area of information. Then we accounted for all these separate areas of information to see if they could be grouped into the stages of the sales pipeline. A total of 63 concepts were extracted. See Appendix C for a total count and relevance of each concept. Using our expert knowledge, we understood the relation between each separate concept in the context of sales. Thus, we were able to group them into the five aforementioned buckets in line with the literature.

Further text mining analysis was conducted to verify the five stages of the sales pipeline. Once the stages were determined, progression through the pipeline could be measured in terms of performance ratios. The best way to calculate progression would depend on the descriptive data from the classification of leads. Once the performance ratios were identified however, there would

be tiered performance groups for each performance ratio. Those tiered performance groups would serve as our outcome variables. The fixing of the performance ratios and the ideal number of tiered performance groups are discussed in the following section (in Phase 1 and Phase 2 respectively).

3.4.2. PROCEDURE TO EXTRACT OUTCOME VARIABLES

3.4.2.1. PHASE 1: TEXT MINING ANALYSIS: Use topic extraction to classify the stages of the sales pipeline. Subsequently classify all result codes into the identified stages.

The first phase involved text mining analysis to classify sales performance in the context of the sales pipeline of an organization. Text mining is a broad field encompassing many procedures and techniques which analyze qualitative textual data to provide both quantitative and qualitative insight. One of its applications is discovering business knowledge from the wealth of information generated from sales and customer relationship related software (Gupta & Lehal, 2009). In the realm of text mining, we are particularly interested in concept extraction, which allow us to identify the different stages of the sales pipeline.

To validate our preliminary findings, Latent Dirichlet Allocation (LDA) was used as a topic modelling technique to extract concepts from the text. LDA as a topic modelling tool generates topics or concepts 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). This makes sense as our Result Code sheet contains tabular data, and we hope to uncover multiple topics from this data via unsupervised machine learning, where each formed topic consists of a mixture of words from various rows in the document. The LDA method is particularly suitable for studies with a large volume of data. (Maskeri, Sarkar & Heafield, 2008; Tirunillai & Tellis, 2014). Indeed, compared

to other topic modelling techniques, LDA was found to be particularly adept at detecting multiple topics from lengthy documents (Lee, Song & Kim, 2010; Maier et al, 2018). This is suitable for our case, as the Result Code sheet is a lengthy document consisting of hundreds of thousands of rows.

When conducting the actual LDA test, we first removed all stop words as a necessary preprocessing step to obtain a more insightful result (Luo, Pan & Zhu, 2017; Zhao et al., 2011). There is no estimate of an optimal number of topics in LDA, as the number of topics is an external parameter which must be experimented with (Elgesem, Steskal, & Diakopoulos, 2015). The best strategy would be to extract multiple topics and see if those topics fit within the five pre-identified themes (i.e., No Contact, Suspect, Prospect, Qualified and Client). We were able to do this using an ontological approach, which seeks to understand what exists. In our view, the different classifications of leads in the pipeline exists as per a priori research on this subject matter. Moreover, the author of this study was able to use his expert knowledge having worked as a lead researcher before to borrow from the empirics to supplement the rational approach. We manually coded the unique Result Codes, assigning them to one of the five stages of the sales pipeline. Insight from topic modelling provided cues on all the different topics of information that could cause a result code to be classified into a certain stage. This allowed us to hand code the various types of result codes into one of the five stages of the sales pipeline, despite the semantic or contextual differences that may exist between them.

To measure the reliability of our classification, we used the test-retest method where we assigned each sales result into one of the five identified stages at two different points of time. A correlation score of above 0.8 between the two classifications meant that there is good reliability

(Vilagut, 2014). Our measurement possesses criterion and construct validities in line with the definitions of the five identified stages (see Section 2.2).

3.4.2.2. PHASE 2: JENKS NATURAL BREAKS OPTIMIZATION: Discretizing performance ratios at each stage of the sales pipeline into levels of categorical performance, which will serve as our output variables.

After having calculated the performance ratios from the identified stages of the sales pipeline, the next phase is to identify the outcome variables. The outcome variables in our study measure different levels of team performance, which is based on the discretization of performance ratios at each stage of the sales pipeline.

Our data does not allow us to extract the formation dates of the sales teams, but it allows us to extract the date of the teams' first interaction with a lead (i.e., when a member of the team first interacted with a lead). Hence, to calculate the performance ratios, we measured the interactions of sales teams with leads from the first to the last interaction.

Once all teams and their performance ratios were listed, we plotted histograms that showed the frequency distribution for each ratio across all teams. Our aim is to discretize the continuous ratio variable into distinct groups. Therefore, we had 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. To do this, we used Jenks Natural Breaks clustering. It is a non-hierarchical iterative partitioning method recommended for dividing observations into a pre-determined number of clusters. It 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, the Jenks Natural Breaks clustering is suitable for classifying one dimensional data while retaining the non-hierarchical attributes.

3.5. PROCEDURE TO BUILD THE CONCEPTUAL MODEL

Once we had extracted both the predictor and outcome variables, we would have to build a conceptual model showing the relationships between each set. To do this, we weighed the directional hypothesis of each predictor on Inside Sales performance based on all prior research conducted on the constructs. This allowed us to hypothesize the direction of effect of each construct on sales performance. Hence, we followed a deductive approach. Please note that for those constructs that were never measured at a team level before, we extended their results at an individual level to hypothesize performance at a team level.

3.6. PROCEDURE TO VALIDATE THE CONCEPTUAL MODEL

MULTINOMIAL LOGISTIC REGRESSION: Extract and logistically regress the predictor variables on the outcome variables, -i.e., the low, medium and high performing groups for each of the performance ratios.

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

Multinomial logistic regression is used when the dependent variable is categorical with more than two levels, as it is with our case. As stated earlier, we are interested in deriving three groups which are characterized by the maximization of their intra-similarity and inter-dissimilarity, and not their size. Multinomial regression does not require the group sizes to be equal (Tabachnick & Fidell, 2007). Additionally, multinomial logistic regression has an advantage in that it does not need the predictor variables to meet requirements of normality, linearity and homoscedasticity (Bayaga, 2010). We are yet to determine the nature of our predictor variables, but it is a safe bet that many of them will not meet the criteria for normality, linearity and homoscedasticity. However, the assumption of non-multicollinearity of variables has to be met for logistic regression. Only VIF values of less than 10 will be accepted, and as such a threshold value has been recommended before (Hair, 2014; Kennedy, 1992).

Logistic regression has the benefit that it can directly produce probabilities which are better for business interpretation. It is a common method for measuring sales performances. Some researchers use logistic regression to measure sales performance where the outcome variables are nominal, and are representative of certain sales success (Liu, Chugh & Noel Gould, 2016). Other researchers frequently use logistic regression to measure sales performance where the outcome variables are ordinal, and are representative of levels of sales success (Warren, 2016; Gilinksy, Newton & Ayler, 2018). The latter is akin to our case. Also, in the sales force management context where the data can be complex and unstructured, data mining techniques such as logistic regression and decision trees are more useful than the simpler linear regression techniques (Albers, Raman & Lee, 2015).

After we identified the three categories of performance for the Suspect, Prospect and Qualification ratios, we ran a multinomial logistic regression model for each ratio that comprises

the eight predictor variables and the three outcome variables. For each hypothesis, we verified if the proposed relationship between the predictor variable and outcome variables is significant in terms of direction and effect. The low performance group was the designated baseline comparison group. The relative probability of a team being in the medium and high performance groups had to be significant for each predictor variable in order to prove the respective hypothesis.

We first checked for overall model fit via chi-square likelihood ratio test at the 0.05 confidence level and the Pseudo R-Squared values. In particular, we looked 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 is set to exemplify an excellent fit (McFadden, 1973). From the classification table, we obtained the accuracy of the models in predicting the outcome performance group. We looked at the Akaike information criterion (AIC) values to see if a balance could be struck between goodness of fit and parsimony. We constructed the Receiver Operating Characteristic (ROC) curves of these different models to see how they compare in terms of diagnostic ability, but also to understand which variables have more predictive ability. The use of ROC curves is heralded due to its summarization of performances across all possible thresholds (Muñoz & Felicísimo, 2004). It really allows us to isolate the chances of predicting a high and medium performing team respectively with respect to the other two performance groups in each case. Finally, to validate our findings, we employed bootstrapping validation where the data is repeatedly sampled using replacements from the original dataset.

As far as the environmental or external factors go when it comes to determining sales performance, none of our main variables are beyond the influence of the company or the employees of the company. However we will use industry as a control variable, which can be categorized as an external factor. As we have two industries, it is important to control for them to see if they have

an effect on the results. It is equally important to control for the number of leads worked on by a team, as our sample contains data from 2005 to 2016. For this reason, all our predictor variables were calculated on a per lead basis, where any measurement would be averaged for all leads worked on by that team. The B2B sector has long sales cycles, so the lead in question takes precedence over the year of operation. Gaps between years of operation signify that contact with leads was paused because of a loss of contact, or that a need could not be met, and that it was only reengaged later on in a different context. Hence for teams who had such gaps in their record for leads, only their history with the lead post gap was considered.

CHAPTER 4: OUTCOME VARIABLE RESULTS

4.1. PHASE 1: TEXT MINING ANALYSIS

4.1.1. IDENTIFICATION OF THE FIVE STAGES

Sales teams work on projects which receive leads. Each Project ID has different Result IDs which correspond to different result codes. In total, there are 595,027 result codes that are used by teams. Result ID is a unique identifier of different outcomes of each call made to a lead. Through text mining, we explored all the result codes to determine how sales teams classified the results of each call. We were able to extract the different stages a lead goes through during its journey through the sales pipeline, namely No Contact, Suspect, Prospect, Qualified and Client. For a definition of each stage, refer to Appendix E.

4.1.2. THE PROCESS USED TO EXTRACT THE FIVE STAGES

In order to identify the stages of the sales pipeline defined above, we looked at the full range of 595,026 result codes irrespective of the frequency of terms. This meant the application of text mining to all 24,746 unique terms that made up those 595,026 terms. When text mining the result codes, there were some cases that were unclassifiable in our framework. So it didn't make any sense to group them under one of our 5 identified stages. The Results Codes that were not counted as one of the five stages include: already a client, post client services, foreign language result, gibberish information (numbers, wildcards), redirectory information, etc. For leads associated with such results, there were other results in the call history that were more meaningful, hence the classification of these leads into one of the five stages was still possible. But when a lead consisted only of non-classifiable results, it was excluded from our study. For the rest of the terms where there was sufficient coherency, we did not want to miss the opportunity to classify them when

possible. Therefore, all 24,746 unique result codes constituted the sample frame used to run the concept extraction.

Running Leximancer yielded 63 concepts as we saw from our initial textual exploration of the data. We then used Latent Dirichlet Allocation (LDA). LDA's bag of words method is best for the short length of the result codes, as each code consists of few words. It 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. We first preprocessed the text by removing punctuation, stop words and whitespaces. Then we plotted a perplexity chart to determine the optimum number of concepts by comparing models with different numbers of topics (see Appendix F). Perplexity is a statistical measure of how well a probability model predicts a sample. Perplexity was lowest at 203 topics, hence a LDA model using 203 topics was run. The 203 generated topics and the top five words of each topic per topic distribution are shown in Appendix G. The keywords are binned into the five identified categories in Table 3.

Table 3

Result Codes: Identification of the Stages using LDA in R

No Contact	Suspect	Prospect	Qualified	Client
• Answering machine • Busy signal • Drop • Leave vm • 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

Just as we did using Leximancer, we were able to successfully bin most of the topics into five bins using LDA.

Looking at both Leximancer and LDA, our identified stages of the sales pipeline do not follow any pattern related to the volume of composition of concepts and topics respectively. Rather, concepts and topics at various rankings in terms of frequency agglomerate to comprise the five identified stages. There were some unassignable concepts. But these concepts were too esoteric in nature or occurred too infrequently in order for them to have an effect on the overall results. It's a safe assumption that wherever the result codes related to those concepts occurred, there would be other result codes for that lead's interaction history which would serve as better classifiers of its stage. The only exception to this was the concept of email. Despite being a major concept extracted in all of our text mining phases, it was hard to determine the stage of an email sent even with more context added by the LDA on top of the Leximancer analysis. Unless there was textual evidence to suggest that prior contact was established via email, all email related results were assigned the No contact stage. Even when in doubt, the No contact stage is a safer option due to it being the lowest in rank. This means that if there were any other results belonging to a higher stage for a lead's call history, it would be rightly assigned to that stage when it came to the tallying of results.

Next, we embarked on a process of manually coding the result codes into one of the five stages. Manually coding after topic modelling is a process commonly used by researchers (Chuang et al., 2015; Jacobi, Van Atteveldt, & Welbers, 2016). We had a clear indication of how the five stages differed from each other based on the literature and based on the topics we obtained from Leximancer and LDA. The subsequent classification of each result code was considered too important a task to be left to automation, especially considering that classifying 24,746 unique terms by hand was manageable. The scrutiny each result code received was worth the human effort. We were able to classify 12,478 unique result codes out of 24,746. This amounted to 78% of all

result codes when accounting for total frequency. When we looked at the Insurance and Marketing & Advertising industries only, it amounted to 99.45% of all result codes.

Apart from the Result IDs, each Project ID also has different LeadStatus IDs, which correspond to different lead statuses. Lead Status is a field that is defined as the name and description of the state or position of the lead. Thus we found it useful to use the lead statuses as a confirmatory classifier along with the result codes in order to classify the stage of the lead.

However, Lead Status was only a secondary classifier because every call history ID for a lead in a project did not have a LeadStatusID. Furthermore, lead status was more about what the salesperson was doing about the lead, rather than what was the actual result of the lead. While ResultID revealed the actual state of the lead, the LeadStatus revealed the activity surrounding the lead which can be descriptive, but offers little value to determining its actual state like Result ID does. As with the result codes, the lead statuses were also subjected to a concept map using Leximancer, and a factor analysis using WordStat and LDA topic modelling using R. Finally, just as we had manually coded the unique result codes, we also manually coded the unique lead status IDs. Like with the result codes, coding the sum of cases was not an insurmountable task, and was worth the human effort for the careful deliberation that goes into each classification. The process is repeated for the lead statuses in Appendices H, I, J, K, L and M respectively. Perplexity was lowest at 39 topics. Thus a LDA model using 39 topics was run. The 39 generated topics and the top five words of each topic per topic distribution are shown in Appendix L. The keywords are binned into the five identified categories in Appendix K.

4.1.3. FINAL OUTCOME OF EACH SALES LEAD

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 the performance of the teams, the lead will be categorized in the last chronological stage out of the five possible stages. This will let us know the final outcome of that lead for that team i.e., if it was in the No contact, Suspect, Prospect, Qualified or Client stage. Only then, can we begin to calculate the performance ratios of a team, after accounting for the final outcomes of all the leads the team has worked on.

The Result Code is the primary lead classifier because it tells us were the lead rests at the moment. The lead status is the secondary classifier as it tells us what is being done about the lead. The lead status is not as succinctly accurate as the result code, so it is used only as a confirmatory classifier. Hence, if a lead status is classified in a lower stage than a lead result (result code), then there is no problem because the higher stage of the lead result assigns that leads its final outcome. However, when a lead status is classified in a higher stage than a lead result (result code), then it is a case that we analyze to see if that particular lead status is significant enough to overturn the final outcome gathered from its result code only.

4.1.4. DESCRIPTIVE STATISTICS FROM PHASE 1

There were 4,237 teams in total. Their distribution according to the five different lead stages is shown in Table 4.

Table 4

No Contact	Suspect	Prospect	Qualified	Client
3957	3889	1850	2821	41
	No Contact + Suspect	**No Contact + Suspect + Prospect**	**No Contact + Suspect + Prospect + Qualified**	**No Contact + Suspect + Prospect + Qualified + Client**
	3741	1727	1207	9

As we calculate progression ratios, we need to consider the number of teams who had leads at a particular stage and all prior stages as well. When we do this calculation for Client and all other stages before it, we see that there are only nine teams that have leads in all five stages including Client. The Suspect, Prospect and Qualified stages had enough teams who had leads in those stages, and all stages before it respectively. Hence, a decision was made to combine Client with Qualified and label the group as Qualified. No Contact was the beginning stage of each lead. Hence the ratios of our three stages are computed in the next section.

4.1.5. MEASURES: OUTCOME VARIABLES

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

Qualification Ratio for a team was calculated by dividing the number of qualified leads by the number of qualified and No Contact leads for that team.

The average suspect, prospect and qualification rate for all teams were 43.7 %, 26.6% and 17.9% respectively.

4.2. PHASE 2: JENKS NATURAL BREAKS OPTIMIZATION

There were 3,736 teams in total for which we had suspect ratios. There were 2,263 teams in total for which we had prospect ratios. There were 1,762 teams in total for which we had qualification ratios. Next, we applied Jenks Natural Breaks Optimization to these ratios to find the natural break points whereby we could classify the teams for each ratio into groups. Each ratio is discretized into two, three, four, five and six classes respectively in Table 5.

Table 5

Classes	Goodness of Variance Fit for Suspect Ratio	Goodness of Variance Fit for Prospect Ratio	Goodness of Variance Fit for Qualification Ratio
2	0.644042	0.8343023	0.75351
3	0.82317	0.9257326	0.903998
4	0.90291	0.9604293	0.948249
5	0.937383	0.976087	0.969252
6	0.957293	0.9849779	0.979266

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, it is worth our effort to segment our outcome variables into the three groups of low performers, medium performers and high performers for each ratio. We see that when we choose four classes, the increase in the GVF is not as much as it is for three classes. Also, interpreting the results would be a tougher task with four classes and it would negate the purpose of discretizing the data in the first place for achieving greater parsimony. Just choosing two classes however sacrifices the huge jump in the GVF that we get with three classes. Thus, three classes is optimum. Our outcome variables are low performers, medium performers and high performers. The three classes for each ratio with their breaking points are shown in Appendix N.

The ordinal outcome variables of low, medium and high performance categories are chosen because of their ability to reflect performance better than the ratio outcome variables. We cannot assume the performance is linearly distributed when it comes to ratio outcome variables, therefore it is not possible to understand the differences in performance levels between each ratio. An incremental increase at one end of the scale may not mean the same thing as an incremental increase on the other end of the scale. Thus, the categorization of teams provides a better representation of team performance with respect to each ratio. Trichotomizing continuous variables is preferred to dichotomization as it reduces inefficiency of lost data due to the transformation process (Gelman & Park, 2009).

CHAPTER 5: CONCEPTUAL MODEL DEVELOPMENT

This chapter covers our fourth research objective. Here we develop a framework for sales performance in Inside Sales based on the team-based constructs identified in the previous sections. While there are many studies on constructs depicting individuals' impact on sales performance, there are few studies that predict the aggregated effect of these constructs with regards to teams (Stewart, 2006). Many constructs that distinguish sales teams are dependent on the individuals that form the team. Even if team level constructs are aggregations from individual level constructs, the predictor-outcome relationships vary between the individual and group levels (Ostroff, 1993). This means that a team is more than the sum of its parts (i.e., individuals).

The constructs used to predict individual sales performance can be categorized as organizational factors, salesperson factors and environmental or external factors (Churchill, Ford & Walker, 1990). The aggregated team level effects of each construct are hypothesized to increase the performance in a team-based setting. Salesperson level constructs include effort and experience, while team size, task input, team goal monitoring, specificity of role, repetition and intra-team communication can be classified as organizational factors. We did not have any environmental or external factors in the model, but the industry of the team was used as a control variable. These constructs are detailed below in the same order they were defined in the Predictors section (see Section 3.4). Each section is concluded with a hypothesis. All the hypotheses are consolidated in our proposed model to assess the drivers for team-based sales performance.

5.1. TEAM SIZE

According to Stewart (2006), findings on Team Size's effect on sales performance are mixed. Arguing against bigger teams, Gooding and Wagner (1985) state that the size of a subunit in an

organization is negatively correlated or not correlated at all with performance. Process losses and free rider effects are blamed for this negative correlation. Mullen, Symons, Hu and Salas (1989) claim that larger group sizes lead to increased dissatisfaction among group members because of greater formalized structures. Arguing for bigger teams, Magjuka and Baldwin (1991) posit that while designing and administering employee involvement programs, team size has a positive impact on sales performance. Larger teams are said to perform better due to greater access to information. Yetton and Bottger (1982) find bigger teams to be better problem solvers and decision makers à la "the best member strategy". By having more members in a team, there is a higher likelihood the a single member of that group comes up with the best decision that results in higher performance.

Kozlowski and Bell (2001) cite the difficulty of measuring the effectiveness of Team Size on performance given that the benefits or a larger team depend on the task and environment. They agree however that evidence seems to suggest that larger teams may be better positioned for success from a resources point of view, but they suffer from loss of coordination. Nieva, Fleishman and Reick (1985) propose a curvilinear relationship between team members and performance, where too few or too many members is less than optimal.

There is a theory that larger teams are more effective because of greater heterogeneity. Magjuka and Baldwin's (1991) findings support such a claim while (Campion et al. (1993) find contrary evidence or no evidence to support such a claim. Perry et al. (1999) state that evidence points to a drop of effective communication with bigger teams. All in all, there is a fair amount of evidence on both sides regarding the appropriate team size for achieving greater sales performance. But the evidence is slightly skewed in favor of smaller teams due to process losses, free rider effects and the increasing difficulty of coordination as stated before.

Finally, Stewart (2006) found team size to be positively related to project and management teams, but not to production teams. The former two differ from the latter in that their tasks are complicated and require interactions with employees and units outside the team in order to attain necessary resources (Sundstrom, DeMeuse & Futrell, 1990). One can see that production teams are similar to Inside Sales teams which have greater autonomy resulting from their interdependence and well defined tasks. Therefore, the size of such teams would be negatively correlated with team performance. In light of that, we posit:

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

5.2. TEAM EXPERIENCE

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. A team is composed of multiple salespersons, and salesperson experience is identified as one of the contributors to greater sales performance via coordination (Cespedes, 1992). Other scholars confirm that salesperson experience leads to greater sales performance via salesperson behavior (Rapp, Ahearne, Mathieu & Schillewaert, 2006; Park & Holloway, 2003). Hence, we posit that:

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

5.3. TEAM EFFORT

Individual effort explains the variance of sales performance in teams (Hunter & Perreault Jr., 2007; Perry et al., 1999). Selling effort mediates the relationship between sales team connectedness and performance (Nowlin, Walker & Anaza, 2017). Selling effort is also found to mediate the relationship between group goal setting and performance (Guzzo & Dickinson, 1996). So it is

understood that effort is a contributor to greater performance. Moreover, 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, Dixon, Chonko & Cannon, 2005). Hence, 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:

H3: Inside Sales teams with greater effort perform better at various stages of the sales pipeline.

5.4. TASK INPUT

From a sales point of view, the input of data by sales personnel is essential to understanding the selling or buying situation (Tanner, Ahearne, Leigh, Mason & Moncrief, 2005). Such input of data is a task by itself, and it has an effect on sales performance via collaboration. Steiner (1976) corroborates the necessity of task input, highlighting its importance in a team-based atmosphere 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 group processes on outcomes (Gist, Locke & Taylor, 1987). Proper fulfillment of tasks is a powerful mechanism to achieve sales performance via cooperation (Ahearne et al., 2008; Yilmaz & Hunt, 2001). Task quality is also found to be a moderator between process and effectiveness in sales teams. We posit that:

H4: Inside Sales teams with higher task input perform better at various stages of the sales pipeline.

5.5. TEAM GOAL MONITORING

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 (T. Rapp et al., 2014). Hence, we are inclined to say that greater team goal monitoring leads to better sales performance. We posit that:

H5: Inside Sales teams with higher team goal monitoring perform better at various stages of the sales pipeline.

El Ansary, Zabriskie and Browning (1993) identify coordination as a dimension of teamwork, which is said to be an important contributor to sales performance. Stewart (2006) finds intra-team coordination to exhibit a positive relationship with performance. Particularly, intra-team coordination leads to greater performance in knowledge-based work environments than in physical work environments. Guzzo and Dickinson (1996) claim that a large part of the success of computer technology comes down to the structuring of the task. Therefore, the success of Inside Sales teams who use LMS is a function of how structured their work process is. Jones et al. (2005) write that sales teams are better equipped than individuals to make better decisions because of the sum of their intelligence and access to more sources of information, but that coordination plays a great role in fulfilling this potential. We see that higher intra-team coordination leads to a greater sales performance. The reflective variables Specificity of Role, Repetition and Intra-team communication also lead to a greater sales performance by virtue of intra-team coordination.

5.6. SPECIFICITY OF ROLE

According to Yilmaz & 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 of team members or specialization thus necessitates the existence of coordination. Such a linkage between the two is corroborated by Dickinson and McIntyre (1997). Hence specialization is an important part 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. We posit that:

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

5.7. REPETITION

Salespeople can become very adept at using sales technology to execute tasks by means of repetition. The effective and habitual use of technology in sales have facilitated collaboration amongst salespeople (Rodriguez & Honeycutt Jr., 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, Williams & Leigh, 2004). Hence, repetition is an important gauge of intra-team coordination, leading to a better sales performance. We posit that:

H7: Inside Sales teams with greater repetition perform better at various stages of the sales pipeline.

5.8. INTRA-TEAM COMMUNICATION

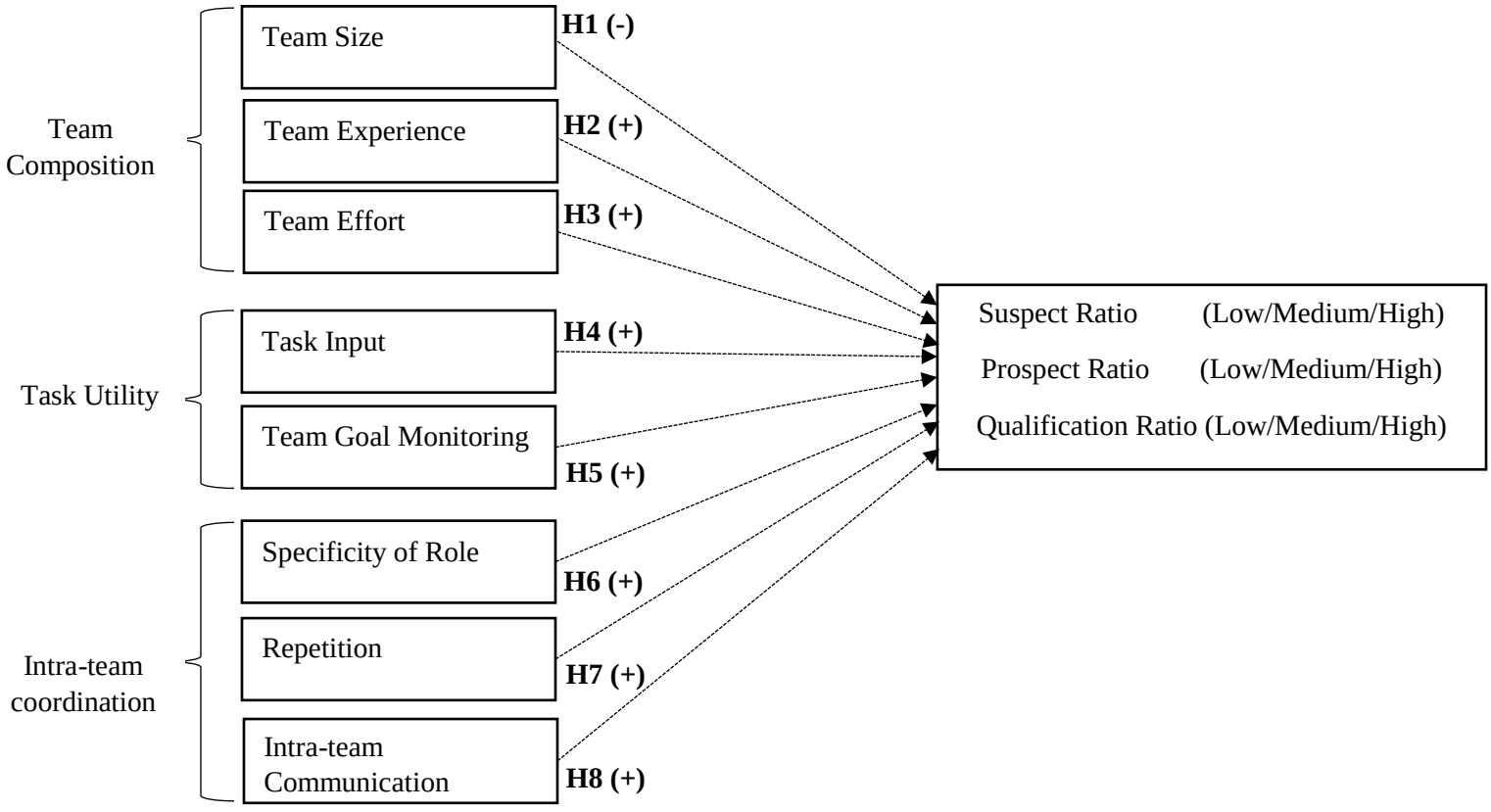
Kiesler and Sproull (1992) found that computer usage leads to more open and direct communication, which results in more equal participation from all group members, leading to

greater productivity. Aiken and Riggs (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.

Our model is depicted in Figure 1. We posit that the observed variables from the three constructs of Quality Group Composition, Task Utility and Intra-team Coordination lead to greater sales performance at three distinct stages of the sales pipeline à la performance ratios, i.e., the suspect ratio, prospect ratio and qualification ratio. For each performance ratio, there will be low performing teams, medium performing teams and high performing teams.

5.9. Figure 1: DRIVERS OF TEAM-BASED PERFORMANCE IN INSIDE SALES



CHAPTER 6: DATA ANALYSIS- MODEL RESULTS

The leads were classified by their highest reached stages. When we looked at the distribution of the leads by their progression, we saw that 93 % of all leads who progressed from No Contact were solitary leads. We define solitary leads as leads who only had one stage, namely: Suspect, Prospect, Qualified or Client, or had No Contact plus one of those stages. Since No Contact is the starting stage for a lead, No Contact plus one of those Stages still constituted as just one stage. See Appendix O for a breakdown of the leads by progression. The fact that there was an overwhelming majority of solitary or one stage leads means that there was not much movement between the stages, but rather the teams were more likely to take a lead to its highest stage in their first call where they were actually able to contact the lead. This makes sense because it gets more and more difficult to move a lead down the sales pipeline.

What this means for our predictor variables is that we would calculate them separately for our Suspect, Prospect and Qualification Ratios. The team variables can be dynamic in nature, and are calculated on the basis of the average of interactions with every lead. Since 93% of leads who progressed are solitary leads, it would make sense to divvy them up while calculating our team variables. For instance, the team variables used to calculate suspect ratio would only be calculated using the average interaction with suspect leads.

6.1. MULTINOMIAL LOGISTIC REGRESSION

6.1.1. CHECKING FOR MULTICOLLINEARITY

The VIF values were checked for the Suspect, Prospect and Qualification ratios respectively. None of them crossed the threshold of 10 as predetermined earlier (see Appendix P). 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 not by much (see Appendix Q). Furthermore, with only nine variables, all of which are relevant to our models capturing team characteristics or interaction with sales leads, sacrificing fit for parsimony did not make sense.

6.1.2. CHECKING FOR OUTLIERS

In our model, the outcome variables are distributed on a ratio scale of 0 to 1, and they are demarcated into three distinct groups based on the strength of their intragroup similarities and intergroup differences. Hence, there is no concept of outliers as the multinomial logistic regression model assumes that the error terms may have an independent and identical value distribution. But there is the scope of having high leverage points of the predictor variables which could have undue influence on our model. Thus, we looked at the Cook's distance to eliminate the high leverage points which had a high influence on our model. We used the recommended cut-off point of four divided by the sample size in each of the three models of performance ratios (Das & Gogoi, 2015). After that, we ran all three models.

6.1.3. RUNNING THE MODELS

6.1.3.1 SUSPECT RATIO

The Suspect Ratio Model was found to be significant at the 0.05 confidence level. With the exception of team experience and industry, all other variables were significant. The model achieved a 58.6% classification accuracy rate as seen in Table 6. It achieved a McFadden pseudo R square of 0.088. Refer to Appendix R for the case processing summary, model fitting information, likelihood ratio tests evaluating each variable as a whole, and the parameter estimates for the medium and high performing teams in reference to the baseline low performing teams. All

significant variables are highlighted in yellow. The Suspect Ratio model was not as good as the Qualification ratio model and the Qualification Ratio model in terms of its predictive ability.

Table 6: Classification of Suspect Ratio Model

	Predicted			
Observed	1	2	3	Percent Correct
1	773	556	8	57.8%
2	436	1388	33	74.7%
3	97	415	30	5.5%
Overall Percentage	35.0%	63.1%	1.9%	58.6%

6.1.3.2. PROSPECT RATIO

The Prospect Ratio Model was also found to be significant at the 0.05 confidence level. With the exception of industry, all other variables were significant. The model achieved a 87.2% classification rate as seen in Table 7. It achieved a McFadden pseudo R square of 0.499. Refer to Appendix S for the case processing summary, model fitting information, likelihood ratio tests evaluating each variable as a whole, and the parameter estimates for the medium and high performing teams in reference to the baseline low performing teams. All significant variables are highlighted in yellow. It was the best performing model out of the three.

Table 7: Classification of Prospect Ratio Model

	Predicted			
Observed	1	2	3	Percent Correct
1	1615	42	1	97.4%
2	107	263	33	65.3%
3	45	62	95	47.0%
Overall Percentage	78.1%	16.2%	5.7%	87.2%

6.1.3.3. QUALIFICATION RATIO

The Qualification Ratio Model was also found to be significant. With the exception of specificity of role and industry, all other variables were significant. The model achieved a 83.3% classification rate as seen in Table 8. It achieved a McFadden pseudo R square of 0.362. Refer to Appendix T for the case processing summary, model fitting information, likelihood ratio tests evaluating each variable as a whole, and the parameter estimates for the medium and high performing teams in reference to the baseline low performing teams. All significant variables are highlighted in yellow. It was the second best performing model out of the three.

Table 8: Classification of Qualification Ratio Model

	Predicted			
Observed	1	2	3	Percent Correct
1	1284	58	3	95.5%
2	157	145	8	46.8%
3	41	27	39	36.4%
Overall Percentage	84.1%	13.1%	2.8%	83.3%

6.1.4. TESTING OF HYPOTHESES

Each hypothesis from the conceptual model development section is evaluated below for all three of our models.

With reference to low performing teams (the baseline group for this study):

Team Size was found to be significant at the 0.05 confidence level for both medium and high performing teams for all three models, namely: Suspect Ratio, Prospect Ratio and Qualification Ratio. Smaller team sizes lead to higher performance ratios in all cases except for medium performing teams for Suspect Ratio.

Team Experience was found to be significant at the 0.05 confidence level for only high performing teams for Suspect and Prospect Ratio, and for both high performing and medium performing teams for Qualification Ratio. More team experience leads to higher performance ratios for Prospect and Qualification ratios, but not high performing teams for Suspect Ratios.

Team Effort was found to be significant at the 0.05 confidence level for both medium and high performing teams for Suspect and Qualification Ratio, and for only medium performing teams for Prospect Ratio. More Team Effort leads to higher performance ratios in all cases.

Task Input was found to be significant at the 0.05 confidence level for both medium and high performing teams for Suspect and Qualification Ratio, and for only high performing groups for Prospect Ratio. More Task Input leads to higher performance ratios in all cases except for high performing teams for Suspect Ratio and Prospect Ratio.

Team Goal Monitoring was found to be significant at the 0.05 confidence level for both medium and high performing teams for Prospect Ratio, and for only high performing teams for Suspect

Ratio and Qualification Ratio. More Team Goal Monitoring leads to higher performance ratios in all cases except high performing teams for Suspect Ratio.

Specificity of Role was found to be significant at the 0.05 confidence level for only medium performing teams for all three models. More Specificity of Role leads to higher performance ratios in all cases except medium performing teams in Suspect, Prospect and Qualification ratios.

Repetition was found to be significant at the 0.05 confidence level for both medium and high performing teams for Suspect and Qualification Ratio, and for only medium performing groups for Prospect Ratio. More repetition leads to higher performance ratios in all cases except medium and high performing teams for Qualification Ratio.

Intra-team Communication was found to be significant at the 0.05 confidence level for both medium and high performing teams for Prospect and Qualification Ratio, and for only high performing groups for Suspect Ratio. More Intra-team Communication leads to higher performance ratios in all cases.

All the above information is captured in Table 9 Green arrows and red arrows indicate positive and negative significance respectively. Empty spaces without arrow indicate non-significance.

Table 9

	Suspect Ratio	Prospect Ratio	Qualification Ratio
Team Size (Medium Perfomer)	↑	↓	↓
Team Size (High Performer)	↓	↓	↓
Team Experience (Medium Perfomer)			↑
Team Experience (High Performer)	↓	↑	↑
Team Effort (Medium Perfomer)	↑	↑	↑
Team Effort (High Performer)	↑		↑
Task Input (Medium Perfomer)		↓	↑
Task Input (High Performer)	↓	↓	↑
Team Goal Monitoring (Medium Perfomer)		↑	
Team Goal Monitoring (High Performer)	↓	↑	↑
Specificity of Role (Medium Perfomer)	↓	↓	↓
Specificity of Role (High Performer)			
Repetition (Medium Perfomer)	↑	↑	↓
Repetition (High Performer)	↑		↓
Intra-team Communication (Medium Perfomer)		↑	↑
Intra-team Communication (High Performer)	↑	↑	↑

6.2. ROC CURVES

Suspect Ratio

The Suspect Ratio model, despite being significant, did not do as well in predicting team performance as the Prospect and Qualification Ratio. All variables more or less closely follow the diagonal reference line. Refer to Appendix U for the area under the curve for each variables. One can notice more of a curve for the variables for high performers, but this pattern is common among all models as high performers are a more distinctive group compared to medium and low performers. Please see figures 2 and 3.

Figure 2: Suspect Ratio Medium Performers

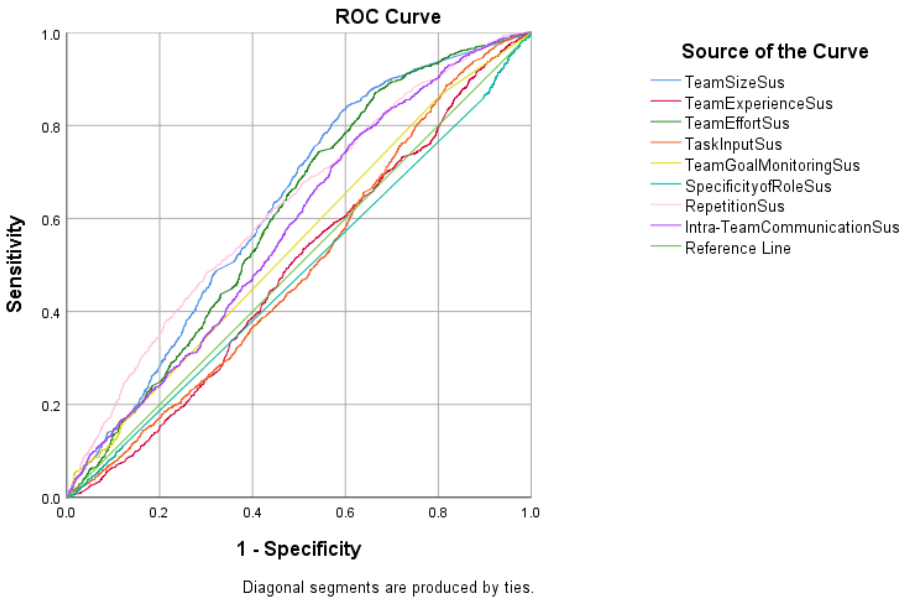
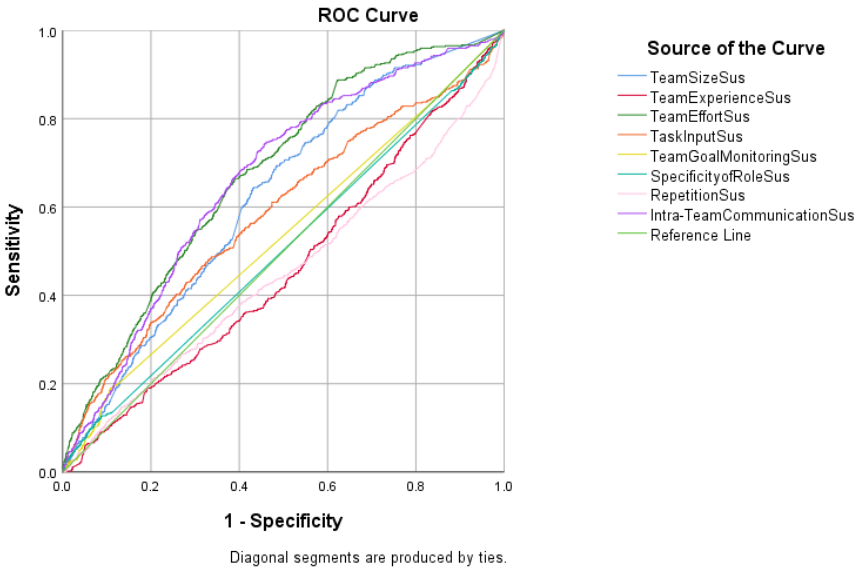


Figure 3: Suspect Ratio High Performers



Prospect Ratio

The Prospect Ratio model achieves the highest prediction accuracy among the three models. For medium and high performers, one can see the high lift of Intra-team Communication and Team Goal Monitoring. Please see figures 4 and 5.

Figure 4: Prospect Ratio Medium Performers

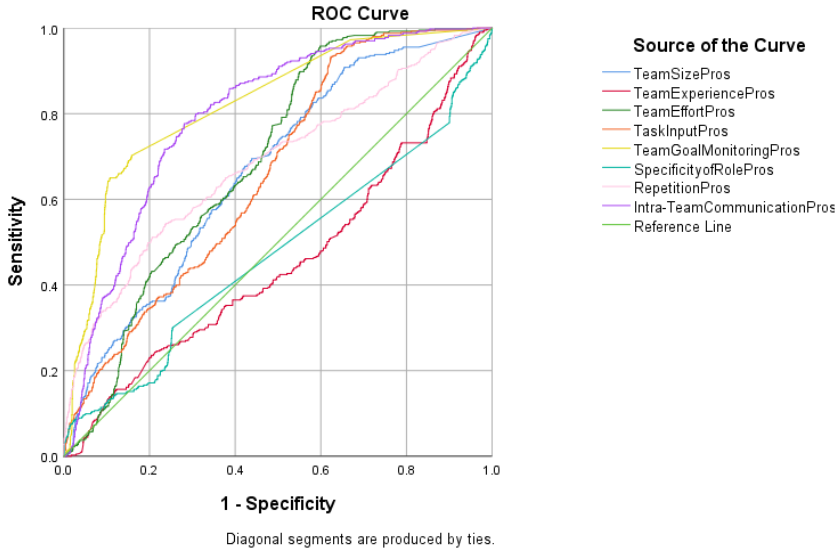
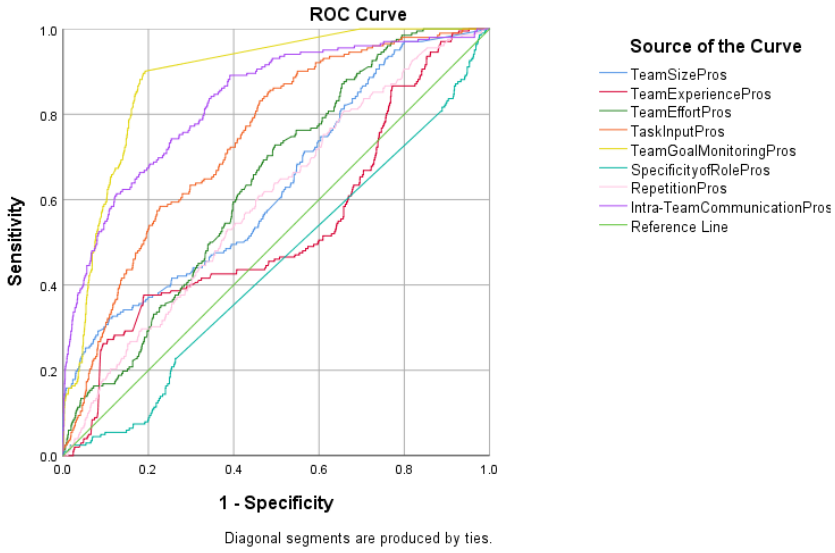


Figure 5: Prospect Ratio High Performers



Qualification Ratio

The qualification ratio model achieves a high prediction accuracy, but not as high as the prospect ratio model. For both medium and high performers, one can see the high lift of intra-team communication and task input. Particularly for high performers, one can also see that Team Experience separates itself from the rest of the pack in terms of its predictive capability. More interestingly for high performers, Repetition and Team Size both have curves with high lifts, but in the other direction. This means the absence of each has a tremendous effect on the true positive rate for high performers. Please see figures 6 and 7.

Figure 6: Qualification Ratio Medium Performers

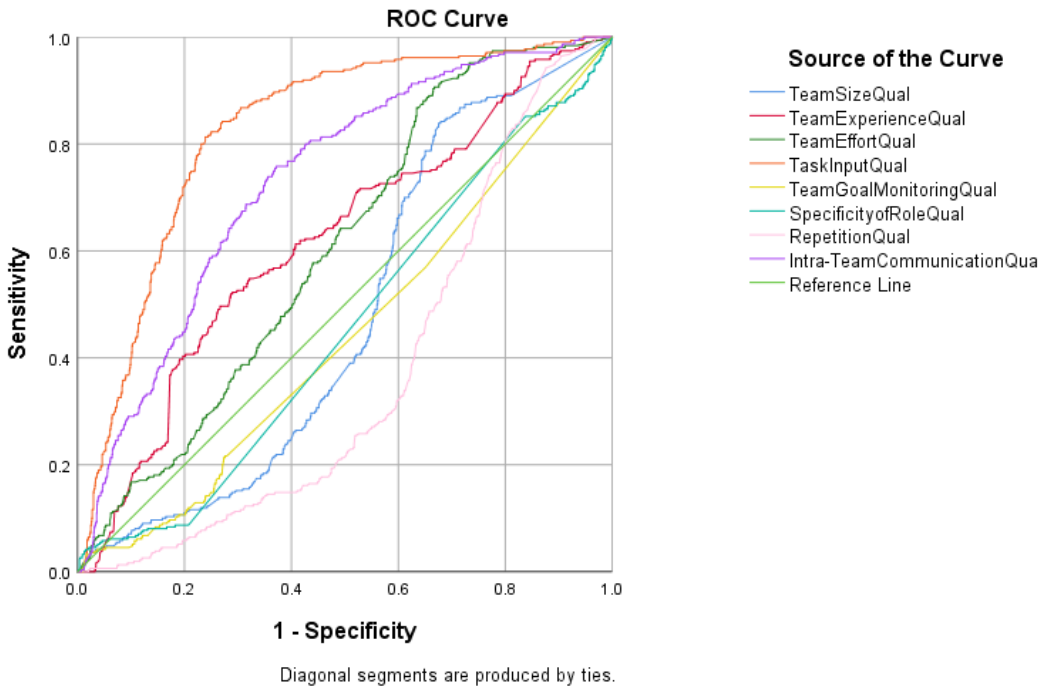
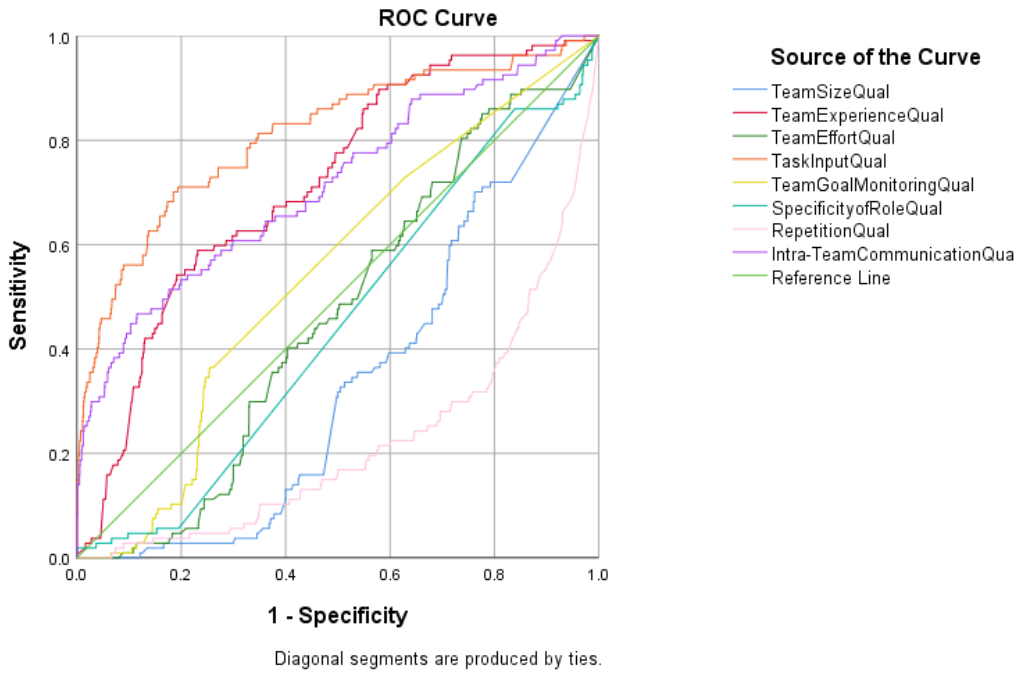


Figure 7: Qualification Ratio High Performers



6.3. VALIDITY

Bootstrapping was performed using 1000 samples at the 95% confidence interval. Refer to Appendix V for the parameter estimates of the variables after bootstrapping. 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 was found to be insignificant for high performers, but Specificity of Role was found to be significant, which was not the case pre bootstrapping. Thus it can be inferred, that our calculations for the Prospect Model was most robust. Elsewhere, there is no cause for concern because in all three stages, there were no cases were the results for both medium and high performing groups were overturned.

CHAPTER 7: CONCLUSION

7.1. KEY FINDINGS

Smaller Sized Teams Do Better in Inside Sales

All directional hypotheses were definitive from the literature with the exception of Team Size. There was enough evidence from the literature to make a case for both bigger and smaller team sizes increasing team performance, with slightly more papers vouching for smaller team sizes. Hence, we hypothesized smaller teams to have better performance. From our study, we saw that to be a medium performing team, bigger teams were better at suspecting, but smaller teams were better at prospecting and qualifying. This makes sense, as one would want more members for lower skilled jobs such as suspecting, compared to prospecting and qualifying which require more skill that cannot be substituted by assigning more team members. However, to be a high performing team, smaller team sizes was the way to go throughout all stages of the sales pipeline (i.e., suspecting, prospecting and qualifying). This means that while more team members may initially be good for suspecting, the number of members in the team will decrease over time to retain the best performers, and those suited for the role of suspecting will get better results in smaller sized teams.

Higher stages of the Sales pipeline require more skills, as reflected by the significance of direction found for Team Composition and Task Utility variables in each model

Except for team size, all our other predictor variables were hypothesized to have a positive effect on team performance. But 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.

To be a medium performing team, team experience was not even significant for suspecting and prospecting, but it was for qualification. Thus, this shows that for jobs requiring more skills, teams would need more experience, whereas for lower level jobs, it would not make a difference. Such a difference shows itself more clearly when looking at high performing teams, where experience was found to be significant for all three stages, but teams with lower experience fared better in suspecting and teams with higher experience fared better in prospecting and qualifying.

Regarding task utility, less task input is better for performance at suspecting and prospecting, but more task input is better for performance at qualifying. Again, this alludes to the increment in skill levels as one moves along the sales pipeline. For suspecting and prospecting, inputting words into the system may be taking away from effort, which is all that it takes to succeed in those levels. Whereas for qualification, mere effort is not enough, and one has to diligently perform other duties such as inputting content words into the leads management systems. The same can be said of Team Goal Monitoring, where in order to be a medium or high performing team, you need less of it for suspecting, but more of it for prospecting and qualifying. So monitoring the progress of goals also takes away from effort in suspecting, but it is important enough a duty at the prospect and qualification stages, where you would need some level of knowledge about the state of the lead. This is because you are not just merely looking to establish contact, but actually the beginning of a relationship. Any prior research on the lead about its internal or external situation may help you in achieving your goal.

Specificity of Role is a detractor in Intra-Team Communication

Regarding intra-team coordination, Specificity of Role was found to be insignificant for high performing teams. It was found to be significant for the medium performing teams, but lesser specificity of role meant better performance, which was contrary to higher intra-team coordination leading to better performances. Thus, it can be surmised that when intra-team communication is talked about leading to better performances, it is Repetition and Intra-Team Communication that is primarily being referred to. Indeed, intra-team coordination unanimously leads to higher performances across the board. Thus irrespective of the stage in the sales pipeline, more intra-team communication is always a good thing. As for Repetition, while more Repetition leads to better performances for suspecting and prospecting, less repetition leads to better performance in qualifying. Thus once again, this constitutes the difference in skills required for the lower level jobs and higher level jobs in the sales pipeline. Whereas for suspecting and prospecting, repeatedly doing something in unison with others may be good for building up expertise, in qualification, it is more about a customized approach which can obtain results.

While the sales pipeline exists, the goal is to convert a lead to a customer in one shot

Lead classification was not the principle goal of our study; identifying the drivers of team-based sales performance was. However, by virtue of classifying each lead by its highest stage, we were able to look at all other stages that lead was in. It turned out that 93% of all leads who progressed from No Contact were stuck in one stage. Thus, while it helps to think of the sales pipeline as a mechanism of progression, in reality it is an artificial construct created by sales professionals to indicate the stage of the lead. The stages are extremely sticky, which is understandable or it would be easy to convert every lead into a customer with just three stages separating a client from a new lead. But it is not, and so it is more likely that a lead is stuck in one stage after a very successful

contact. So it becomes imperative for the salespeople to do their best in their first successful contact attempt. It also makes sense to develop specialized teams who are only suited to either suspect, prospect or quality. All three are important and would be better off with specialized teams attending to them. Our findings also reflect that different variables are needed for each model. Suspecting does not need experience and team goal monitoring like prospecting and qualifying do. Both suspecting and prospecting do not need task input like qualifying does, but they need repetition, which qualifying does not.

7.2. CONTRIBUTIONS

The overarching contribution of this study is team-based selling optimization in Inside Sales. Inside Sales practitioners are better off knowing that smaller teams are more effective for selling (a much contested issue in the past, with researchers split on the verdict), and that it is better not to bother suspecters (i.e., salespeople dealing with suspects) with other tasks such as task input, and team goal monitoring which may hinder their process of becoming specialized at calling leads. These tasks should be left up to prospectors or qualifiers, who need more experience (of doing activities other than just calling) and less repetition (just expanding effort on calling) to succeed.

Inside Sales researchers are better off knowing what the team-based factors that affect sales performance are. We provide a comprehensive model which captures not only previously studied team-based factors, but also four new factors which have never been studied at a team level before, namely Effort, Task input, Specificity of Role and Repetition. We show their effect on the different stages of the sales pipeline as it is relevant to the inside sales process, something that has never been done before. Hence, we analyze the team-based factors' predictive abilities on three different types of sales performance, namely suspecting, prospecting and qualifying.

7.2.1. CONTRIBUTIONS TO PRACTICE

This study contributes to the field of sales management by understanding what makes sales teams successful based on the teams' nature and their interaction with sales leads. It does this via measuring the impact of team variables on specific stages of the sales pipeline, and hence ventures into territory unscathed by research. Thus, it has great practical implications. Due to the increased operational costs of maintaining an external salesforce, Inside Sales has gained prominence where data analytics is used to best support such inside sales teams (Gessner & Scott Jr., 2009). Ours would be an example of such a study, whereby we built a predictive model stating what things can be improved in a team-based setting for a greater chance at succeeding. Even though the model is hypothesis based, it is through the comprehension of the important success factors by which managers can strategize their sales process. There is a need for research in sales optimization beyond just conceptual studies and anecdotal case studies (Avlonitis & Panagopoulos, 2009). Empirical studies on the engineering of the sales process such as ours provide salespeople with the insights to better suspect, prospect and qualify leads.

It is true that it is harder to predict successful suspecting, compared to prospecting and qualifying. Nevertheless, one can use the insight that it is more about effort (e.g., volume of calls), and less about checking progress or completing specific tasks such as inputting a comment into the LMS. The classification tables and ROC curves of prospect and qualification ratios show that a much higher prediction accuracy can be achieved for those two acts. It is interesting that while inputting comments continues to have a negative impact on prospecting, checking progress has a positive effect on it. In fact, team goal monitoring via checking progress, and intra-team communication are the strongest predictors of successful prospecting. Regarding qualification, Task input, Intra-team coordination and Team Experience are its strongest predictors. Repetition

also has a negative effect on it, which is not the case with suspecting and prospecting. Based on this knowledge, companies can allocate different teams for different tasks. More experienced members who have a more customized approach to each lead would do the qualifying, whereas less experienced members who have more a direct approach of dealing the same way with every lead would do the suspecting and prospecting.

7.2.2. CONTRIBUTIONS TO RESEARCH

Our study looks into the much neglected field of team sales, using team-based predictors to measure team-based performance. Whereas many studies have focused on individual salesperson factors to measure sales performance, it remains to be seen if those same individual factors can be aggregated at a team level to measure sales performance (Verbeke, Dietz & Verwaal, 2011). This is what we did with the variables Team Effort, Task Input, Specificity of Role, and Repetition while also identifying and analyzing priori team-based variables such as Team Size, Team Experience, Team-goal monitoring, and Intra-team communication.

Apart from the classification posed by Churchill, et al. (1990), there is an alternate category of constructs that measure sales performance, which is equally applicable to our case, namely sales technology usage. The advent of sales technology has placed increased demands on companies to employ teams that will be able to maximize the efficiency of SFA use (Devine, Clayton, Philips, Dunford, & Melner, 1999; Rangarajan, Jones & Chin, 2004).The computerization of the workplace has meant the “expansion of research on groups that use computers in their work” (Guzzo & Dickinson, 1996, p.320). Indeed, constructs that we are attempting to measure bar group size are the result of some type of interaction with the LMS used by the company. This study indirectly confirms the positive effect of SFA acceptance and usage on sales performance which has been advocated in many papers (Ahearne et al., 2004; Hunter & Perreault Jr, 2006). Due to the fact that

the measurement of every construct except team size was dependent upon the salespeople's usage of SFA, proven hypotheses not only indicate the existence of the proposed relationships but also the validity of SFA usage overall.

Hunter and Perreault Jr. (2007) take the sales technology angle of measuring sales performance by measuring how it is swayed by different usage levels of sales technology. Sales technology usage levels are measured using the paradigms of infrequent and frequent, and sporadic and routine. Similarly, all of our predictor variables with the exception of group size are derived from how or how often one uses the LMS. While there has been a lot of research comparing technology-using groups to non-technology or face to face groups, there has not been much comparison within technology using sales teams as to what factors enable better outcomes (Guzzo & Dickinson, 1996). This study enabled us to do just that as we study thousands of teams to uncover possible performance drivers à la our predictor variables.

To conclude, our study is new for two reasons. First, the study is conducted using secondary data exclusively. Thanks to our industrial partner, we have access to records of companies from multiple industries interacting with sales leads. The survey method, which was the main method of data collection in most of the prior studies, has many risks, including self-selection bias, Hawthorne effect, acquiescence bias and extremity bias (Zikmund, Babin, Carr & Griffin, 2013). But with secondary data, there is no worry about the motivation or incentives of the person participating in the survey, or any chance of response error caused by the interviewer if it is an onsite survey. There is also no chance of retrospective bias because there is no dependence on the person's memory and objectivity to truthfully answer questions, but rather the data is captured by the LMS in the very act of performing the duty on the part of salespeople. Second, to the best of our knowledge, our study is the only one that measures sales performance at multiple levels of the

sales pipeline. There have been numerous measures for sales performance used in the past, from which we chose the acquisition of a new customer. While such a measure has been used as an outcome variable in the past (Virtanen, Parvinen & Rollins, 2015; Gessner & Scott Jr., 2009), there have been no attempts to measure sales performance at demarcated stages of the sales pipeline before the acquisition happens. By segmenting stages of a sales pipeline, we monitored the performance of sales teams on each lead at distinct points of its journey, from the time of its entry into the sales pipeline to the time it becomes a client or falls out of the pipeline.

7.3. LIMITATIONS & WAY FORWARD

From a broad perspective, there are some team constructs which we cannot measure from our data, but are highly relevant in explaining why a team may or may not succeed. The personalities of each team member, particularly their preference for teamwork, would be great information to have in order to understand what leads to performance beyond the reflective variables of coordination, task utility and favorable group composition. Such constructs are extremely difficult to measure using a data source that is not explicitly created for the purpose of measuring the said constructs. Hence, a survey research method would be best suited to accomplish this in the realm of quantitative studies.

Shea and Guzzo (1987) define task interdependence as the degree of task-driven interaction between group members. Task interdependence necessitates coordination. There is a lot of literature on task interdependence, so it would be appropriate if we could measure the level of task interdependency for each team for such a project that focuses on the reflective variables of intra-team coordination. But we are unable to do so with the data at our disposal because each company can have its own organizational setup to dictate the level of interdependency each task mandates. Antecedents of task interdependence include the use of technology, work rules and proximity of

members. While we do not have data on the work rules and proximity of members of organizations, we know that they use a common technology, which in this case is the LMS.

Task-driven interaction is an important mediator between group constructs and sales outcome (Gully, Devine & Whitney, 1995). This makes sense given it manifests itself in intra-team coordination, which is defined by the many-task driven interactions that occur between team members. We previously established how intra-team coordination leads to sales performance. We also established how the reflective indicators of quality of group composition lead to sales performance via coordination (Cespedes, 1992; Perry et al., 1999). Hence measuring task interdependence of teams would strengthen the overall validity of our model because of its pervasiveness in the literature and its possible mediation effects by way of intra-team coordination. For future studies in this field, again a survey measure would be better suited to capture this variable.

In terms of specificity of the results, there is a lot left to be desired because correlation does not equate to causation. There could be a number of third variables which could explain the covariance of the construct and the outcome. To mitigate this, we use the three control variables lead source, year and industry. It is possible that salespeople become more used to the LMS over the years to build up their competency. It could also reveal that over time salespeople learn to not input data in some of the fields, as they don't perceive them to be useful to the final outcome. Also, our industrial partner has a client base comprising of multiple industries. These industries can easily have different patterns of data input into the system or different team characteristics, and so the industry was used as a control variable. While it was found to be non-significant, we were only dealing with two industries, namely: Insurance and Marketing & Advertising. So we are only

limited to these two industries for external validity. For future studies, it would be better if more industries from the B2B sector could be included in the study.

In order to truly prove causation, future studies can try experimental research where team based inside sales performance is checked pre and post administration of a particular construct. This would meet the sequential condition necessary to prove causation. However, such an experiment would be more costly and less time efficient. But it would definitely lend more credibility to the claims of some variables being better predictors of sales performance than others.

It is always a daunting task to come up with measures that fully encapsulate respective constructs. Especially for the reflective variables of task utility and intra-team coordination, we are heavily dependent on recorded inputs in the LMS. But our study passes the test of criterion validity, because there have been plenty of studies which use data input into a computer system to measure constructs relating to task utility. They include studies such as Straub, Limayem and Karahanna-Evaristo (1995) who had measures very similar to this study such as computer recorded system usage to measure variables relating to task utility. Rap et al. (2014), Weinstein & Mullins (2012) and Ahearne et al., (2008) similarly incorporate archival sales data from SFA systems in their studies. For measuring intra-team coordination, we find experts who say that collaboration, which is a grander notion of coordination, can only be measured by adoption of collaboration tools (Hwang, 2013), which in our case is the LMS. LMS providers claim collaboration/coordination as a benefit of using their software, especially amongst marketing and sales teams. Hence, it can be argued that coordination can be in fact measured through system usage, by the act of Specificity of Role, Repetition and Intra-team communication.

Regarding group composition, size and experience are straightforward measures that do not need any proxies. As for effort, its measurement is already justified in the measures section. But

nevertheless, the intra-team coordination variables Specificity of Role, Repetition and Intra-Team Communication are limited in the sense that they are dependent on just three roles and content words from two fields. If industry and academia are more serious about uncovering such attributes from secondary data, they must design LMS to capture such data. Only if such systems are designed with the purpose of capturing such data, can we have an accurate measurement of our intended constructs. Until then, we will depend on proxies.

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APPENDICES

A

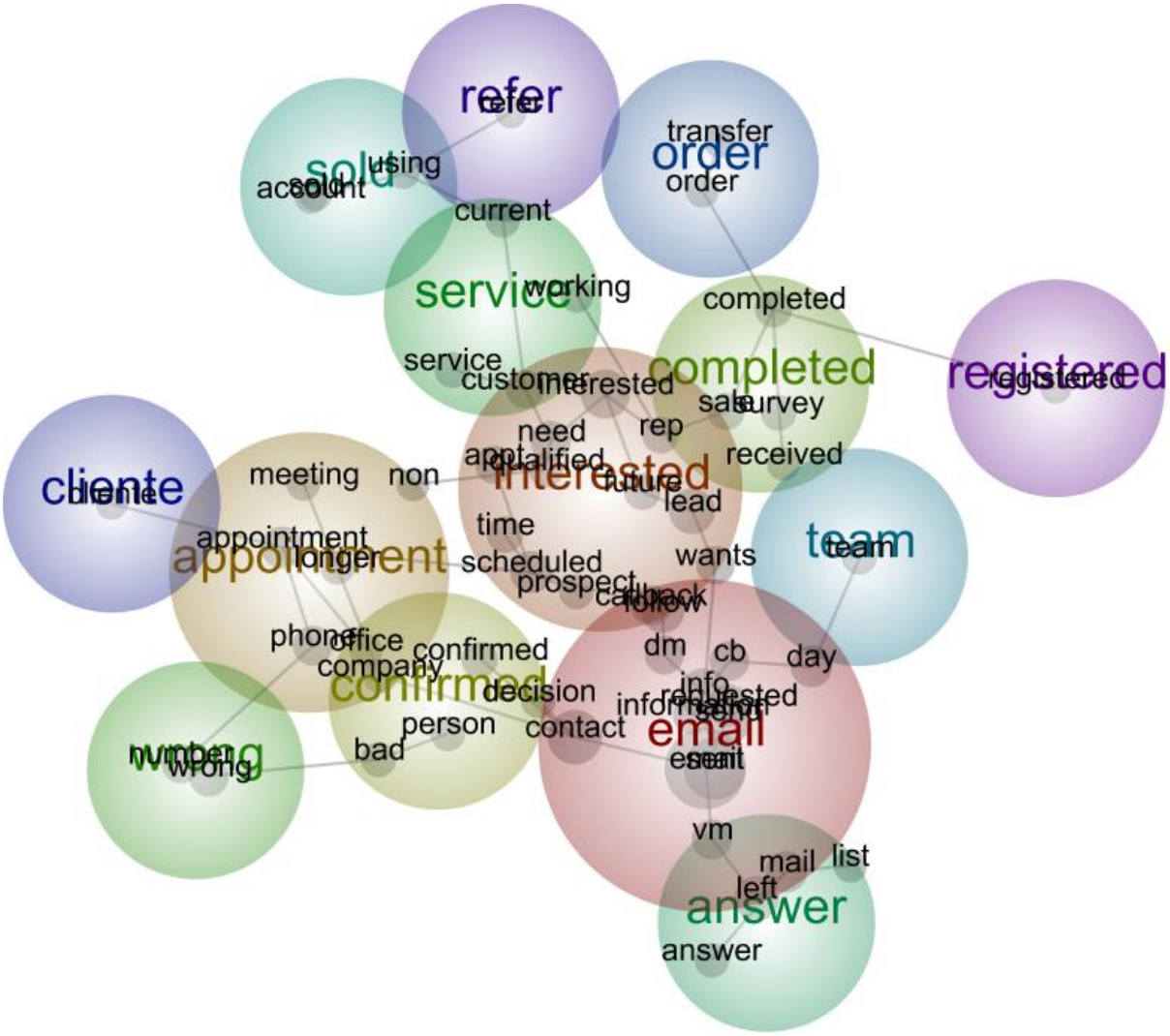
Database	
Web of Science	**Objective 1** Types of Sales Performance sales process broken down into stages ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales performance*" OR "sales performance*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales pipeline*" OR "sales pipeline*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales process*" OR "sales process*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales funnel*" OR "sales funnel*") AND ("team*" OR "group*") **Objective 2** Team-based predictors of sales performance optimal team structure for selling ("team selling*" OR "group selling*") AND ("sales performance*" OR "sales outcome*" OR "sales result*") ("team design*" OR "team structure*" OR "team dynamics*" OR "team feature*") AND ("sales performance*" OR "sales outcome*" OR "sales result*") ("sales teams*" OR "team selling*") AND antecedents to sales performance (antecedent* OR predictor*) AND (team* OR group*) AND (Sales* performance*)
Scopus	**Objective 1** Types of Sales Performance sales process broken down into stages ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales performance*" OR "sales performance*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales pipeline*" OR "sales pipeline*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales process*" OR "sales process*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales funnel*" OR "sales funnel*") AND ("team*" OR "group*") **Objective 2** Team-based predictors of sales performance optimal team structure for selling ("team selling*" OR "group selling*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")

[redacted]	("team design*" OR "team structure*" OR "team dynamics*" OR "team feature*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")
	("sales teams*" OR "team selling*") AND antecedents to sales performance
	(antecedent* OR predictor*) AND (team* OR group*) AND (Sales* performance*)
	Objective 1
	Types of Sales Performance
	sales process broken down into stages
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales performance*" OR "sales performance*") AND ("team*" OR "group*")
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales pipeline*" OR "sales pipeline*") AND ("team*" OR "group*")
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales process*" OR "sales process*") AND ("team*" OR "group*")
ProQuest	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales funnel*" OR "sales funnel*") AND ("team*" OR "group*")
	Objective 2
	Team-based predictors of sales performance
	optimal team structure for selling
	("team selling*" OR "group selling*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")
	("team design*" OR "team structure*" OR "team dynamics*" OR "team feature*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")
	("sales teams*" OR "team selling*") AND antecedents to sales performance
[redacted]	(antecedent* OR predictor*) AND (team* OR group*) AND (Sales* performance*)
	Objective 1
	Types of Sales Performance
	sales process broken down into stages
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales performance*" OR "sales performance*") AND ("team*" OR "group*")
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales pipeline*" OR "sales pipeline*") AND ("team*" OR "group*")
Ebsco-Business Source Complete	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales process*" OR "sales process*") AND ("team*" OR "group*")
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales funnel*" OR "sales funnel*") AND ("team*" OR "group*")
	Objective 2
	Team-based predictors of sales performance
	optimal team structure for selling
	("team selling*" OR "group selling*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")
	("team design*" OR "team structure*" OR "team dynamics*" OR "team feature*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")
	("sales teams*" OR "team selling*") AND antecedents to sales performance

[redacted]	(antecedent* OR predictor*) AND (team* OR group*) AND (Sales* performance*)
IEEE Explore	**Objective 1** Types of Sales Performance sales process broken down into stages ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales performance*" OR "sales performance*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales pipeline*" OR "sales pipeline*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales process*" OR "sales process*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales funnel*" OR "sales funnel*") AND ("team*" OR "group*") **Objective 2** Team-based predictors of sales performance optimal team structure for selling ("team selling*" OR "group selling*") AND ("sales performance*" OR "sales outcome*" OR "sales result*") ("team design*" OR "team structure*" OR "team dynamics*" OR "team feature*") AND ("sales performance*" OR "sales outcome*" OR "sales result*") ("sales teams*" OR "team selling*") AND antecedents to sales performance
[redacted]	(antecedent* OR predictor*) AND (team* OR group*) AND (Sales* performance*)
Scholars Portal Journal	**Objective 1** Types of Sales Performance sales process broken down into stages ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales performance*" OR "sales performance*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales pipeline*" OR "sales pipeline*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales process*" OR "sales process*") AND ("team*" OR "group*") ("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales funnel*" OR "sales funnel*") AND ("team*" OR "group*") **Objective 2** Team-based predictors of sales performance optimal team structure for selling ("team selling*" OR "group selling*") AND ("sales performance*" OR "sales outcome*" OR "sales result*") ("team design*" OR "team structure*" OR "team dynamics*" OR "team feature*") AND ("sales performance*" OR "sales outcome*" OR "sales result*") ("sales teams*" OR "team selling*") AND antecedents to sales performance
[redacted]	(antecedent* OR predictor*) AND (team* OR group*) AND (Sales* performance*)
Google Scholar	**Objective 1** Types of Sales Performance

	sales process broken down into stages
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales performance*" OR "sales performance*") AND ("team*" OR "group*")
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales pipeline*" OR "sales pipeline*") AND ("team*" OR "group*")
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales process*" OR "sales process*") AND ("team*" OR "group*")
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales funnel*" OR "sales funnel*") AND ("team*" OR "group*")
	Objective 2
	Team-based predictors of sales performance
	optimal team structure for selling
	("team selling*" OR "group selling*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")
	("team design*" OR "team structure*" OR "team dynamics*" OR "team feature*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")
	("sales teams*" OR "team selling*") AND antecedents to sales performance
[redacted]	(antecedent* OR predictor*) AND (team* OR group*) AND (Sales* performance*)
	Objective 1
	Types of Sales Performance
	sales process broken down into stages
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales performance*" OR "sales performance*") AND ("team*" OR "group*")
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales pipeline*" OR "sales pipeline*") AND ("team*" OR "group*")
	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales process*" OR "sales process*") AND ("team*" OR "group*")
JStor	("classification*" OR "category*" OR "stage*" OR "level*") AND ("sales funnel*" OR "sales funnel*") AND ("team*" OR "group*")
	Objective 2
	Team-based predictors of sales performance
	optimal team structure for selling
	("team selling*" OR "group selling*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")
	("team design*" OR "team structure*" OR "team dynamics*" OR "team feature*") AND ("sales performance*" OR "sales outcome*" OR "sales result*")
	("sales teams*" OR "team selling*") AND antecedents to sales performance
[redacted]	(antecedent* OR predictor*) AND (team* OR group*) AND (Sales* performance*)
Journals	Journal of Applied Psychology, The Journal of Personal Selling & Sales Management, Journal of Marketing, The Journal of Business & Industrial Marketing, Journal of the Academy of Marketing Science, Journal of Business Ethics, European Journal of Marketing, Journal of Marketing Theory and Practice, Journal of Marketing Research, information processing & management, information resources management journal

B



The Sentences-per-block option was set to one since our text segments are no more than a sentence on average. We expect each case to contain enough information within it for it to be classified to a category. The languages French and Spanish were added to the stop word list, as we are dealing with English only (as dictated by our data). The total number of concepts to be extracted was left

at automatic, which allows Leximancer to extract the naturally emergent number of concepts from the data.

C

Concepts Generated from Result Codes using Leximancer

Word-Like	Count	Relevance
email	1656	100%
contact	1289	78%
sent	940	57%
lead	804	49%
appointment	768	46%
interested	745	45%
left	668	40%
info	587	35%
send	489	30%
follow	439	27%
callback	438	26%
interest	431	26%
mail	400	24%
appt	387	23%
wrong	375	23%
customer	355	21%
phone	328	20%
vm	298	18%
cb	297	18%
client	295	18%
number	291	18%
dm	281	17%
scheduled	269	16%
sold	267	16%
wants	262	16%
information	235	14%
requested	234	14%
day	228	14%
days	227	14%
sale	227	14%
answer	213	13%
future	209	13%
time	206	12%
completed	206	12%
team	196	12%
prospect	195	12%
current	193	12%
rep	187	11%

confirmed	187	11%
need	186	11%
request	180	11%
complete	180	11%
survey	174	11%
needs	167	10%
schedule	160	10%
registered	160	10%
qualified	158	10%
company	158	10%
decision	155	09%
service	154	09%
list	153	09%
person	151	09%
meeting	146	09%
bad	144	09%
sales	139	08%
order	137	08%
received	133	08%
working	132	08%
non	129	08%
longer	128	08%
transfer	124	07%
account	107	06%
use	98	06%

D

Suspect Ratio

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	6061.327			
General	5977.679[b]	83.648[c]	8	.000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

Prospect Ratio

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	2205.981			
General	2009.774[b]	196.207[c]	8	.000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

Qualification Ratio

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	1326.905			
General	1249.462[b]	77.443[c]	8	.000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

E

Following our text analysis process, the five identified stages are defined as follows:

No Contact: This is the 1st stage of the sales pipeline. This stage signifies that the salesperson was unable to contact the sales lead. All leads automatically start at this stage, whether they progress to the next stage or not depends on if any meaningful contact is established with the lead where 1) There is rejection 2) There is no rejection. Not progressing from this stage means that the sales cycle for the lead in question never started. **Any language pertaining to:** left voicemail/message, retry at a particular time, not available, tried for a certain number of times, busy signal, no answer, no contact, intentional skipping of contact, call back etc.

In addition to not being able to contact a person, two other scenarios also apply to this classification: duplicates and wrong number. Such language refers to pre-existing administrative problems, and not problems related to the activity of the salesperson. Hence it would not be fair to classify them as suspect on the grounds of being rejected, because the rejection is not due to the skills or execution of the salesperson but administrative issues. **Any language pertaining to:** wrong number, invalid, duplicates, incorrect contact, bad number, etc.

Suspect: This is the 2nd stage of the sales pipeline. Act of suspecting signifies that a meaningful contact with the lead has been made which involves rejection or no further progress. Thus, all reasons for rejection are classified under suspected. Rejection in turn can be of two types: 1) Rejection by the target. **Any language pertaining to:** Not interested, refused, rejected, already purchased, satisfied with current, hung up, never contact again, too busy, etc. 2) Rejection by the salesperson. Any language pertaining to: Not qualified/disqualified, already sold to, no longer exists, bad fit, too “something”, etc. It is also possible, that after establishing meaningful contact, there is no outright rejection, but a cessation of progress nonetheless. Such instances are also

counted as suspects, as they are not due to administrative issues, but has more to do with the activity of the salesperson in developing further progress. **Any language pertaining to:** could not get past gatekeeper, contact not there, language barrier, research needed, etc.

For our study, this is the base level from which progression will be measured. Hence it is important to exactly specify what types of leads are classified under this category. This is why leads such as duplicates and wrong numbers were not included as suspects, because teams could be unfairly penalized for getting a higher proportion of such leads which would then affect their subsequent ratios used to measure progress.

Prospect: This is the 3rd stage of the sales pipeline. Act of prospecting signifies that a meaningful contact with the target has been made which involves non-rejection or further progress. If there is no rejection, then all other reasons that may signal wanting to continue discussions are included in the Prospected Stage, short of committing to an actual activity where a sale may be discussed. **Any language pertaining to:** Strong interest, wanting quote, needing help, wanting to talk later, indecisiveness, requesting more info, rescheduling, updated, verified, spoke to decision maker, future interest/potential, needs " something", set up callback, profiled, nurture, looking to "something", partially complete, waiting on "something", etc.

A sales lead moving to prospect means that it has escaped initial rejection. This is to the merit of the salesperson, for being able to establish some sort of relationship with the lead without getting rejected. But that does not mean that a lead cannot be rejected at this stage. What often happens is that the lead stops responding (becomes dead), only later on into the conversations is it determined that there is not a current fit for whatever reason, or refuses to participate in an activity that might lead to a sale. But it is still to the credit of the salesperson for having been able to progress the conversation to this stage. Henceforth, such advanced form of rejections are also classified under

prospects. **Any language pertaining to:** dead, cancelled, withdraw, would not like “something”, decline, etc.

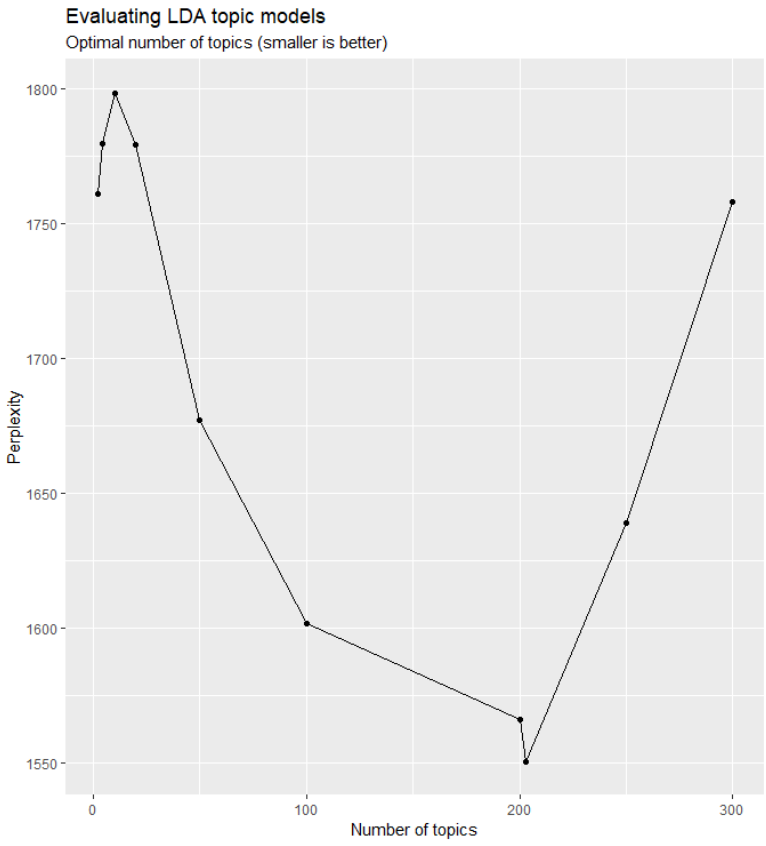
Qualified: This is the 4th stage of the sales pipeline. Act of qualifying signifies an agreement made by the lead to move one step closer into entertaining the prospect of becoming a client by participating in a certain sales activity. It does not merely rest on discussions or need for information anymore, but rather agreeing to a next step from which a potential sale can either be won or lost. **Any language pertaining to:** Face-to-face meeting, confirmed appointment/registration/meeting, agreed to a next step, demo/appointment scheduled, hot/warm lead, presentation/pitch complete, qualified, affirmative answers, intention to purchase, survey completed, opportunity, met with “someone”, quote sent, proposal sent, set up webinar, etc. It also involves an even more advanced form of rejection at this step, which translates to not becoming a client or completing the sales cycle. **Any language pertaining to:** Offer declined, lost to competitor, etc.

A lead moving to qualified means, that it has progressed to a more concrete stage which is based on an actual sales activity other than just talk about determining a fit or the salesperson selling the product. The same rejection symptoms from the prospect stage still apply to this stage, but albeit at a lower rate. So a lead can still go cold after making it thus far, but as before, it is to the credit of the sales person for having been able to progress the conversation to this stage.

Client: The 5th and last stage of the sales pipeline. Advancing to this stage signifies a successful conversion of a lead to a sale, and the completion of the sales cycle for that sales lead. **Any language pertaining to:** The account has been closed, a sale has been made, acceptances of offers, won, sale, deal, client, retained etc.

If a lead is successfully converted to a client, than it is to the full credit of the salesperson for having converted that lead. Once a sale has been made, we treat it as the achievement of the goal. Any forms of cross selling or up selling are seen as different efforts, as thus mark the beginning of a separate sales cycle.

F



G

topic	term	beta
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1	webinar	0.184564
1	detail	0.067885
1	staff	0.061521
1	head	0.04455
2	future	0.292151
2	prospect	0.274881
2	spoke	0.194288
2	potential	0.093546
2	attendee	0.012953
3	info	0.580539
3	requested	0.249265
3	refusal	0.036688
3	gatekeeper	0.03453
3	access	0.009593
4	event	0.235721
4	trial	0.216535
4	free	0.117861
4	member	0.076746
4	page	0.032891
5	answer	0.371587
5	2nd	0.24305
5	one	0.098155
5	machine	0.070111
5	find	0.053752
6	month	0.399619
6	conflict	0.065691
6	cycle	0.065691
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6	base	0.03832
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7	asked	0.130346
7	ever	0.043449
7	cooloff	0.038018
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8	disconnected	0.041668
8	residence	0.020574
8	disco	0.014696

8	replacing	0.014696
9	busy	0.278266
9	signal	0.110147
9	dealer	0.101451
9	line	0.081122
9	place	0.057972
10	upsell	0.076258
10	presented	0.046928
10	rest	0.046928
10	patient	0.041062
10	motivo	0.041062
10	ring	0.041062
11	contract	0.28379
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11	drop	0.098848
11	failed	0.079716
11	sched	0.051019
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13	researched	0.037739
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15	transfered	0.073051
15	fedex	0.062615
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16	insurance	0.091345
16	firm	0.076121

16	followed	0.068509
16	recently	0.064954
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17	uses	0.139378
17	ups	0.133802
17	partner	0.122652
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19	apt	0.108299
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20	hours)	0.052398
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21	informacion	0.051806
22	por	0.186321
22	quiere	0.11361
22	cliente	0.07597
22	sale:	0.0409
22	cancelation	0.031811
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24	black	0.050012
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24	friday	0.035723
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25	**********	0.195585
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31	case	0.124419
31	message,	0.07178
31	...	0.047854
31	delivered	0.033498
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32	tech	0.137807
32	support	0.08917

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32	progress)	0.064851
33	account	0.44515
33	yes-	0.109105
33	callbacks	0.069827
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33	corrected	0.056735
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34	**data	0.081121
34	planning	0.076731
34	lft	0.067704
34	msg	0.06064
35	thanks	0.02352
35	04-Mar	0.017672
35	duplicated	0.01764
35	interest/uncooperative	0.01176
35	printed	0.01176
35	clock	0.01176
35	hostile	0.01176
35	sorti	0.01176
35	modified	0.01176
35	coming-specify	0.01176
35	300	0.01176
36	client	0.662048
36	life	0.072778
36	l..	0.03052
36	s.d.	0.028172
36	recontacter	0.021129
37	move	0.262761
37	calendar	0.098045
37	fup	0.094123
37	registering	0.054905
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38	plus	0.139416
38	action	0.123926
38	pour	0.089071
38	package	0.054217
38	rappeler	0.046472
38	artwork	0.046472

39	gift	0.22841
39	policy	0.123994
39	single	0.071786
39	students	0.055471
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40	register	0.375559
40	live	0.299432
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41	email	0.241746
41	sms	0.105296
41	lvm	0.084237
41	influencer	0.075813
41	f/u	0.071602
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42	red	0.020331
42	cell	0.014981
43	order	0.518882
43	placed	0.136985
43	permanent	0.049813
43	previously	0.049396
43	dist	0.012474
44	rep	0.424536
44	paid	0.095637
44	issues	0.079309
44	feedback	0.05365
44	recruiter	0.034989
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45	cuenta	0.062471
45	cancelada	0.058533
45	enviado	0.039022
45	movil	0.039022
45	interesado.	0.039022
46	direct	0.212788
46	less	0.106877
46	times	0.091195
46	debit	0.08251

46	mandate	0.047769
47	buyer	0.16705
47	producto	0.110101
47	caller	0.075932
47	competencia	0.036766
47	del	0.033995
48	end	0.242825
48	queue	0.214878
48	status	0.147806
48	video	0.031673
48	message-	0.028154
48	moves	0.028154
49	refer	0.403926
49	credit	0.208478
49	subscription	0.048862
49	interest/	0.026135
49	advance	0.019545
50	interesado	0.086378
50	commission	0.063123
50	interesse	0.056478
50	cita	0.053156
50	recibida	0.049891
51	qualified	0.373976
51	calls	0.087847
51	low	0.085337
51	keep	0.067767
51	incoming	0.042668
52	registered	0.488086
52	donation	0.119629
52	donate	0.028711
52	appropriate	0.028711
52	attending,	0.019141
53	schedule	0.306042
53	presentation	0.158088
53	msg	0.116671
53	complete-	0.085124
53	self	0.054723
54	business	0.372772
54	good	0.182997
54	got	0.162664
54	lead,	0.044055

54	ezpay	0.020333
55	tax	0.148003
55	reset	0.115113
55	fiche	0.071261
55	disqualified	0.071261
55	debt	0.060297
56	return	0.244073
56	recibido	0.081358
56	cliente	0.059139
56	activacion	0.050066
56	chase	0.043808
56	getting	0.043808
57	left	0.325028
57	message	0.22957
57	mail	0.175691
57	voice	0.138266
57	final	0.058949
58	show	0.268311
58	rescheduled	0.24498
58	missed	0.10888
58	appoinment	0.038886
58	better	0.023331
59	email	0.185485
59	packet	0.092203
59	aahoa	0.030734
59	tina	0.023051
59	contact/email	0.023051
59	drop/	0.023051
60	reason	0.193843
60	emailed	0.191358
60	form	0.173962
60	given	0.084496
60	processing	0.047218
61	new	0.494531
61	website	0.092601
61	details	0.066988
61	replacement	0.065018
61	resigned	0.033494
62	wrong	0.517215
62	disconnected	0.1039
62	health	0.059286

62	process	0.055197
62	type	0.040887
63	current	0.335026
63	satisfied	0.147484
63	cliente	0.125936
63	services	0.080115
63	desea	0.034595
64	e-mail	0.497212
64	upcoming	0.024861
64	offered	0.024861
64	renter	0.024861
64	autres	0.019888
64	pbp	0.019888
65	working	0.312661
65	already	0.240424
65	speaking	0.075723
65	tomorrow	0.03664
65	sage	0.029312
66	con	0.202917
66	oficina	0.109913
66	promesse	0.101458
66	area	0.076094
66	descontento	0.064821
67	refus	0.200237
67	rendez	0.074598
67	vous	0.074598
67	placement	0.058893
67	sans	0.054967
68	book	0.173783
68	intro	0.167685
68	deal	0.088194
68	sem	0.060976
68	attended	0.060976
69	service	0.259918
69	attending	0.201345
69	agent	0.122637
69	program	0.117146
69	enough	0.040269
70	avec	0.077916
70	refuse	0.057026
70	lender	0.057026

70	considering	0.053462
70	autre	0.049988
71	want	0.268228
71	equipment	0.103165
71	bid	0.05674
71	solicita	0.046137
71	cliente	0.027176
72	face	0.328786
72	reschedule	0.311707
72	appt.	0.149448
72	tbc	0.02135
72	passed	0.017763
73	close	0.396874
73	online	0.167908
73	interesa	0.036715
73	uso	0.033582
73	messages	0.024423
74	card	0.241594
74	found	0.208143
74	pledge	0.189559
74	internal	0.059469
74	donated	0.037168
75	attend	0.214959
75	hipaa	0.127729
75	said	0.084114
75	term	0.062307
75	going	0.04673
75	activated	0.04673
76	available	0.412801
76	voice	0.110764
76	mail,	0.095262
76	dropped	0.067477
76	answer,	0.067477
77	wants	0.421102
77	quote	0.183515
77	now	0.144191
77	store	0.048642
77	price	0.045879
78	research	0.24367
78	assign	0.158227
78	leads	0.136075

78	someone	0.110759
78	broker	0.056889
79	interested	0.838347
79	products	0.05175
79	unsure	0.018112
79	qualified,	0.007762
79	acquired	0.006469
80	initial	0.105827
80	cancellation	0.071963
80	acct	0.050797
80	solar	0.050797
80	error	0.050797
81	already	0.572208
81	engaged	0.082055
81	second	0.067589
81	push	0.046668
81	local	0.016093
82	call)	0.108045
82	(pre	0.063026
82	deposit	0.063026
82	voicemail/	0.063026
82	structure	0.063026
83	information	0.404392
83	follow-	0.148515
83	updated	0.144937
83	talked	0.066206
83	contacts	0.042944
84	hour	0.173887
84	erronea	0.040574
84	/call	0.028981
84	persona	0.028981
84	birthday	0.017389
84	disconected	0.017389
84	union	0.017389
85	user	0.305774
85	submitted	0.128564
85	choice	0.104241
85	cash	0.069494
85	fleet	0.048646
86	invalid	0.115327
86	booking	0.105716

86	validated	0.100911
86	discuss	0.091301
86	emails	0.086495
87	1st	0.556567
87	mins	0.07951
87	(email)	0.039755
87	hit	0.034076
87	xsell	0.028396
88	full	0.111896
88	added	0.097551
88	code	0.088251
88	put	0.068859
88	speak	0.057383
89	company	0.319997
89	longer	0.288448
89	interested-	0.099154
89	exit	0.022535
89	exists	0.015774
90	refused	0.280306
90	profile	0.225463
90	amp	0.127966
90	courtesy	0.085311
90	strong	0.048749
91	meeting	0.46859
91	financial	0.04546
91	question	0.027976
91	changes	0.024532
91	fuera	0.024479
92	will	0.48024
92	provided	0.06701
92	hung	0.061426
92	consider	0.046535
92	que	0.02606
93	needs	0.484228
93	confirmation	0.13609
93	still	0.085452
93	linkedin	0.075957
93	club	0.025319
94	agreement	0.210339
94	currently	0.210339
94	arrange	0.082633

94	customers	0.052585
94	receiving	0.045073
95	otro	0.136507
95	prior	0.122137
95	saved	0.071846
95	engagement	0.071846
95	closing	0.064661
96	yes	0.777832
96	seminar	0.077783
96	load	0.022224
96	study	0.00926
96	pr<e9>sent	0.007408
97	days	0.534604
97	check	0.135029
97	expressed	0.030352
97	interest-	0.030313
97	screen	0.024801
98	warm	0.389559
98	email-	0.102516
98	identified	0.087138
98	annual	0.051258
98	reply	0.041006
98	cards	0.041006
98	client,	0.041006
99	sales	0.313763
99	review	0.185509
99	manager	0.130544
99	passed	0.0546
99	property	0.050385
100	recontact	0.087379
100	w/contact	0.087379
100	now,	0.07767
100	rfq	0.058252
100	qualification	0.058252
101	voicemail	0.523764
101	reached	0.257934
101	eoq	0.036848
101	(contact	0.010528
101	contacting	0.010528
102	general	0.299144
102	returned	0.106275

102	discussion	0.059042
102	prospecting	0.051169
102	vc/nc	0.031489
103	make	0.132156
103	rco	0.097681
103	samples	0.074697
103	carrier	0.051713
103	cant	0.051713
104	par	0.187274
104	d<e9>j<e0>	0.077352
104	argumente	0.073281
104	suivi	0.065139
104	validation	0.056997
105	phone	0.622402
105	application	0.135393
105	risk	0.024249
105	works	0.022229
105	nothing	0.018187
106	first	0.200696
106	specific	0.154635
106	give	0.082253
106	kick	0.082253
106	amount	0.072382
107	request	0.341592
107	later	0.142992
107	get	0.067524
107	cancel	0.061566
107	mailed	0.051636
108	record	0.367447
108	attempted	0.097986
108	problem	0.069407
108	cleansed	0.032662
108	evening	0.028579
109	proposal	0.18785
109	lost	0.120988
109	brad	0.055952
109	(cb)	0.047991
109	contact)	0.047977
110	conversation	0.313679
110	owner	0.199278
110	different	0.081187

110	connection	0.047974
110	filled	0.047974
111	funds	0.091631
111	legacy	0.04998
111	vin	0.03332
111	north	0.03332
111	south	0.02499
112	signed	0.171617
112	using	0.160021
112	add	0.146106
112	yes,	0.071893
112	refund	0.032468
113	hors	0.137378
113	yet	0.131133
113	cible	0.049955
113	temp	0.049955
113	unhappy	0.037467
114	budget	0.166912
114	immediate	0.087848
114	church	0.074671
114	travel	0.070279
114	met	0.065886
115	timeframe	0.09402
115	box	0.079555
115	mgr	0.06509
115	awaiting	0.057858
115	mo.	0.057858
116	recorded	0.02857
116	achat	0.017142
116	installed	0.017142
116	fait	0.011505
116	1hour	0.011428
116	candidate,	0.011428
116	months.	0.011428
116	non-committal	0.011428
116	vcal	0.011428
116	fax/email	0.011428
116	ignore	0.011428
116	lunch-	0.011428
116	scope	0.011428
116	published	0.011428

116	re-send	0.011428
117	needed	0.432083
117	additional	0.168344
117	encouraged	0.067338
117	short	0.03928
117	fourth	0.033669
118	conversion	0.170907
118	titular	0.089523
118	imposible	0.081384
118	duplicado	0.056969
118	contactar	0.048831
119	list	0.411823
119	remove	0.132372
119	attempts	0.091189
119	ownership	0.047065
119	max	0.029416
119	profiled,	0.029416
120	file	0.257511
120	sends	0.193133
120	chaser	0.059426
120	whitepaper	0.034665
120	queue	0.034374
121	email	0.568805
121	sent	0.387593
121	via	0.02417
121	(contact)	0.000879
121	flyer/cb	0.000879
122	set	0.407861
122	time	0.236591
122	date	0.102924
122	interested,	0.041437
122	pitched	0.03208
123	hours	0.488916
123	take	0.191315
123	denied	0.0744
123	apply	0.031886
123	contact/call	0.021257
123	physician	0.021257
124	bond	0.030469
124	precall	0.030469
124	imposibilidad	0.024456

124	acudir		0.024375
124	outstanding		0.024375
125	n<e3>o		0.11384
125	vanilla		0.071899
125	problemas		0.059916
125	telefone		0.047933
125	nao		0.041941
125	ocupado		0.041941
126	renewal		0.241016
126	pass		0.107688
126	funded		0.066664
126	stips		0.05128
126	complaint		0.05128
127	interest		0.822528
127	regular		0.024586
127	lit		0.022349
127	conv.		0.011176
127	class		0.008815
128	wrong#		0.113408
128	sur		0.065658
128	eow		0.065658
128	whole		0.041782
128	versement		0.041782
129	faxed		0.099836
129	spanish		0.078442
129	retenida:		0.06418
129		10%	0.060615
129	disc		0.057049
129	descuento		0.057049
130	lead		0.763216
130	hot		0.091671
130	requires		0.024517
130	custom		0.017055
130	months)		0.009593
131	test		0.165486
131	solution		0.126948
131	visita		0.072527
131	fecha		0.047606
131	gestor:		0.040805
132	opportunity		0.337733
132	talk		0.185753

132	interest,	0.090062
132	verification	0.084433
132	funding	0.056289
133	rappel	0.300517
133	active	0.189214
133	ste	0.074202
133	secretaire	0.048231
133	indisponible	0.029681
134	payment	0.315112
134	declined	0.252089
134	tecan	0.048477
134	stage	0.038783
134	aca	0.033935
134	doe	0.033935
135	tarjeta	0.291418
135	contrata	0.052807
135	#NAME?	0.033441
135	estado	0.033441
135	cr<e9>dito	0.028664
136	contact,	0.260667
136	appel	0.09413
136	modif	0.065167
136	annule	0.057926
136	retour	0.057926
137	another	0.239257
137	verified	0.200035
137	work	0.133356
137	progress	0.066678
137	reassign	0.0353
138	waiting	0.249851
138	enrollment	0.060309
138	practice	0.056001
138	medical	0.056001
138	doc	0.051693
139	contact	0.947896
139	abr	0.003335
139	locate	0.002501
139	aktualisiert	0.001667
139	availalbe	0.001667
139	mat<e9>riel	0.001667
139	renouvel<e9>	0.001667

140	call	0.668159
140	back	0.294812
140	ams	0.005345
140	keeper	0.003289
140	gate	0.002842
141	months	0.33825
141	purchase	0.158648
141	lead-	0.152661
141	plans	0.125721
141	#NAME?	0.029934
142	product	0.24762
142	plan	0.233863
142	invitation	0.072222
142	promo	0.034392
142	successful	0.03282
143	send	0.599803
143	drip	0.134998
143	done	0.084374
143	mos	0.037125
143	chasing	0.015187
144	project	0.172288
144	moved	0.172288
144	school	0.172288
144	won	0.055378
144	forwarded	0.049225
145	contacted	0.494365
145	wish	0.045775
145	(progress)	0.045774
145	previously	0.028383
145	ken	0.027465
145	call-back	0.027465
145	organizer	0.027465
146	admin	0.278759
146	date/time	0.063354
146	thank	0.063354
146	cust.	0.063354
146	task	0.050683
147	weeks	0.249867
147	language	0.079745
147	inquiry	0.063796
147	barrier	0.042531

147	coms	0.037214
147	medicare	0.037214
148	group	0.205349
148	forward	0.108078
148	coverage	0.086463
148	early	0.054039
148	hospital	0.054039
149	required	0.296579
149	testing	0.164766
149	consult	0.061199
149	provide	0.051784
149	comment	0.047076
150	calling	0.162332
150	set	0.135073
150	telephone	0.114587
150	statement	0.062068
150	wait	0.047745
150	worth	0.047745
151	rdv	0.194991
151	hrs	0.10928
151	c/b	0.101475
151	ncrt	0.083261
151	touch	0.065048
152	web	0.176953
152	link	0.152545
152	auto	0.146444
152	registration	0.143393
152	resend	0.122036
153	completed	0.35814
153	survey	0.313604
153	duplicate	0.100205
153	rejected	0.044536
153	blocked	0.01299
154	just	0.13357
154	req	0.094792
154	buy	0.073248
154	meet	0.064631
154	today	0.051705
155	booked	0.278685
155	corporate	0.194084
155	referred	0.109483

155	location		0.084601
155	inbound		0.074648
156	response		0.197333
156	verify		0.156706
156	old		0.145098
156	negative		0.10447
156	recall		0.10447
157	appt		0.627502
157	set		0.13759
157	ordered		0.073935
157	fly		0.009479
157	tag		0.009408
158	sold		0.524986
158	year		0.141594
158	student		0.050102
158	paperwork		0.02614
158		$199	0.021784
159	week		0.341311
159	sending		0.119253
159	see		0.098692
159	interested-wants		0.03701
159	value		0.032876
160	within		0.192541
160	transferred		0.162456
160	email)		0.120338
160	unreachable		0.114321
160	renew		0.07822
161	pending		0.489814
161	approval		0.089626
161	requests		0.082358
161	opened		0.073689
161	vmail		0.030342
162	need		0.434164
162	person		0.34442
162	source		0.029106
162	correct		0.021829
162	contact/		0.021829
163	sin		0.067111
163	telefono		0.04945
163	llamar		0.049063
163	cambio		0.045918

163	reg	0.038854
164	due	0.119023
164	candidate	0.098619
164	invoice	0.088417
164	gave	0.06842
164	closer	0.064612
165	may	0.142093
165	small	0.099239
165	sign	0.094729
165	sell	0.07443
165	bought	0.065408
166	made	0.416004
166	welcome	0.108371
166	note	0.104875
166	docs	0.076856
166	skipped	0.055933
167	purchased	0.172145
167	recently	0.163199
167	system	0.157556
167	competitor	0.081696
167	enrolled	0.052519
168	email	0.294346
168	send	0.256634
168	merchant	0.159602
168	referral	0.141362
168	sent,	0.02508
169	update	0.219922
169	unable	0.170655
169	stop	0.07226
169	partial	0.069118
169	trying	0.062835
170	high	0.148125
170	empresa	0.0948
170	convert	0.05925
170	cost	0.05925
170	#NAME?	0.0474
170	sub	0.0474
170	std	0.0474
171	dead	0.202397
171	reach	0.195168
171	unavailable	0.122884

171	rsvp	0.079513
171	unable	0.067518
172	pitch	0.166129
172	home	0.162518
172	outbound	0.057784
172	session	0.050561
172	competition	0.039727
173	fit	0.195999
173	pay	0.10584
173	step	0.10192
173	sit	0.08624
173	(bdc)	0.07448
174	conference	0.187524
174	x-mailout	0.037505
174	facilitated	0.025003
174	prospects	0.025003
174	pausa	0.018752
175	text	0.216535
175	donor	0.149909
175	deceased	0.055522
175	nrp	0.04997
175	occupe	0.033313
176	transfer	0.488035
176	changed	0.072005
176	employees	0.056004
176	buying	0.056004
176	mark	0.044003
177	day	0.247652
177	retry	0.21163
177	team	0.20375
177	letter	0.061913
177	change	0.043618
178	closed	0.355068
178	skip	0.173911
178	hold	0.090578
178	deja	0.036231
178	delete	0.032608
179	target	0.170378
179	right	0.141981
179	cust	0.102227
179	draft	0.051113

179	rebuttal	0.051113
180	outside	0.157218
180	happy	0.120226
180	employee	0.055489
180	criteria	0.046241
180	geo	0.041617
180	mobile	0.041617
181	called	0.378335
181	confirm	0.119678
181	comments	0.088793
181	turn	0.054048
181	large	0.038606
182	nurture	0.168647
182	providers	0.099655
182	issued	0.061326
182	aaron	0.030663
182	region	0.030663
183	last	0.1846
183	result	0.133676
183	contactado	0.070021
183	anyone	0.050924
183	savings	0.038193
184	customer	0.610552
184	previous	0.065861
184	like	0.035601
184	owned	0.02136
184	quality	0.01958
185	cancelled	0.375908
185	incorrect	0.085434
185	taken	0.064075
185	created	0.064075
185	care	0.059804
186	callback	0.778831
186	oui	0.041996
186	coberturas	0.01718
186	exact	0.009545
186	certified	0.007636
187	sponsor	0.102721
187	exhibitor	0.093383
187	vocal	0.05603
187	impossible	0.05603

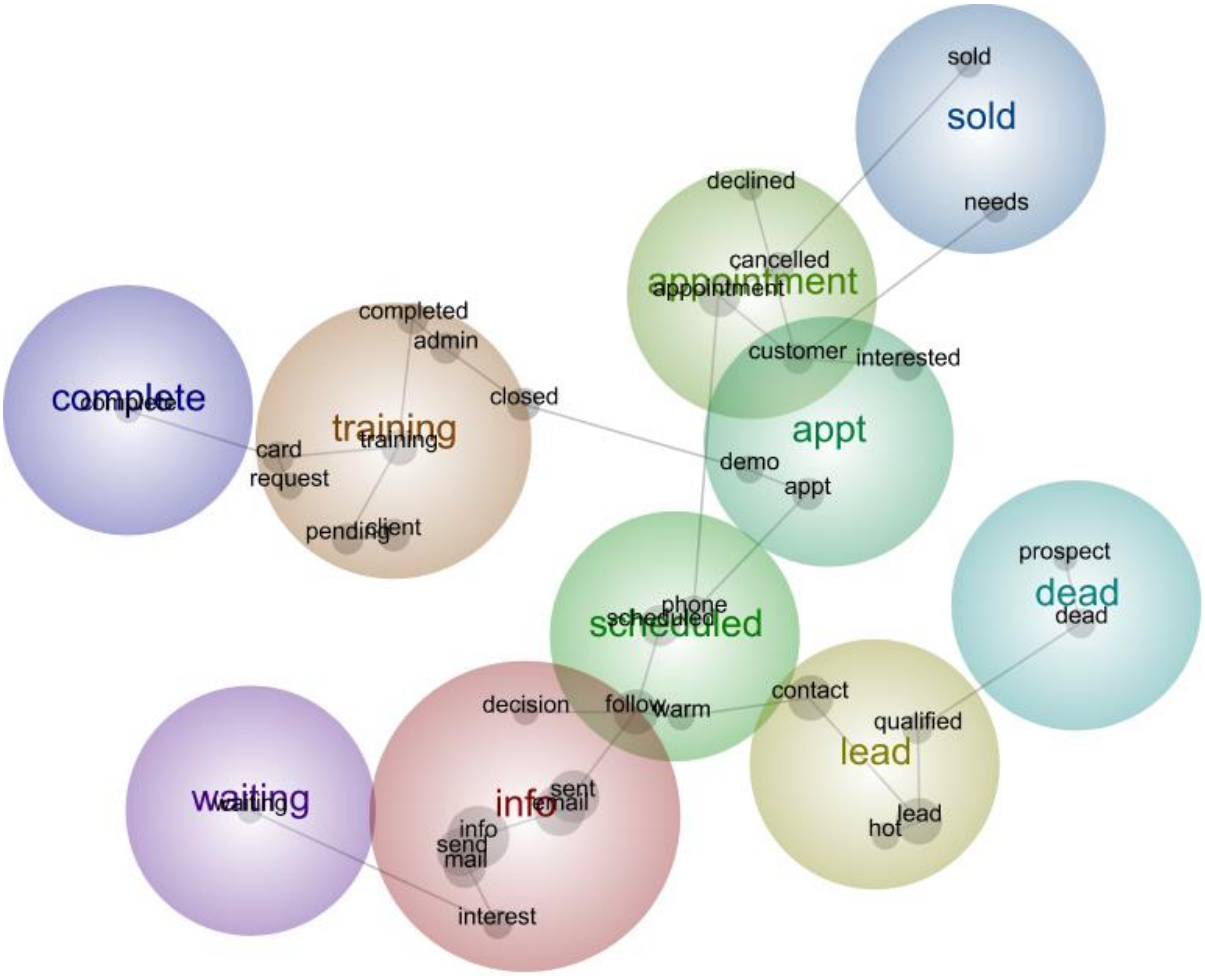
187	joindre	0.037353
188	offer	0.231491
188	notes	0.206799
188	post	0.145068
188	report	0.061731
188	decline	0.046298
189	please	0.247191
189	questions	0.141649
189	profiled	0.091655
189	answered	0.088878
189	explain	0.083323
190	pas	0.314566
190	faux	0.048394
190	car	0.031093
190	cont.	0.02823
190	int<e9>ress<e9>	0.02823
191	accept	0.106556
191	sendout	0.084123
191	gen	0.078515
191	ameriprise	0.050474
191	exchange	0.050474
192	bad	0.399915
192	campaign	0.160622
192	state	0.04917
192	windows	0.039336
192	experience	0.026224
193	received	0.481345
193	bill	0.057597
193	selling	0.057597
193	invoices	0.045255
193	int	0.032912
194	numero	0.140516
194	membership	0.120442
194	renewed	0.080295
194	tel	0.066912
194	promotion	0.046839
195	decision	0.381597
195	maker	0.250012
195	min	0.084214
195	pci	0.060529
195	later,	0.036844

195	pricing		0.036844
196	open		0.121817
196	invite		0.110538
196	email,		0.06542
196	market		0.06542
196	qualify		0.063165
196	blind		0.063165
197	non		0.308351
197	visit		0.075781
197	site		0.073168
197	valid		0.062715
197	sup		0.04965
198	incomplete		0.161304
198	listed		0.077665
198	tpv		0.059742
198	oficina:		0.059742
198	condiciones		0.047794
198	o-ans		0.047794
199	sale		0.388343
199	complete		0.2655
199	ready		0.093123
199	activation		0.031701
199		8821	0.023776
200	surveys		0.117598
200	star		0.044099
200	ambassador		0.036749
200	groupe		0.036749
200	d<e9>cision		0.036749
200	telesales		0.036749
201	scheduled		0.520542
201	next		0.209021
201	reminder		0.068334
201	f2f		0.062304
201	179d		0.017268
202	fixed		0.127543
202	prequal		0.070857
202	uninsurable		0.035429
202	9f.		0.035429
202	medicaid		0.035429
203	positive		0.313871
203	followup		0.305612

203	renewing	0.082598
203	reason-list	0.049559
203	replied	0.024779

H

Concept Map for Lead Status generated using Leximancer



I

Lead Status: Identification of the Stages from Leximancer

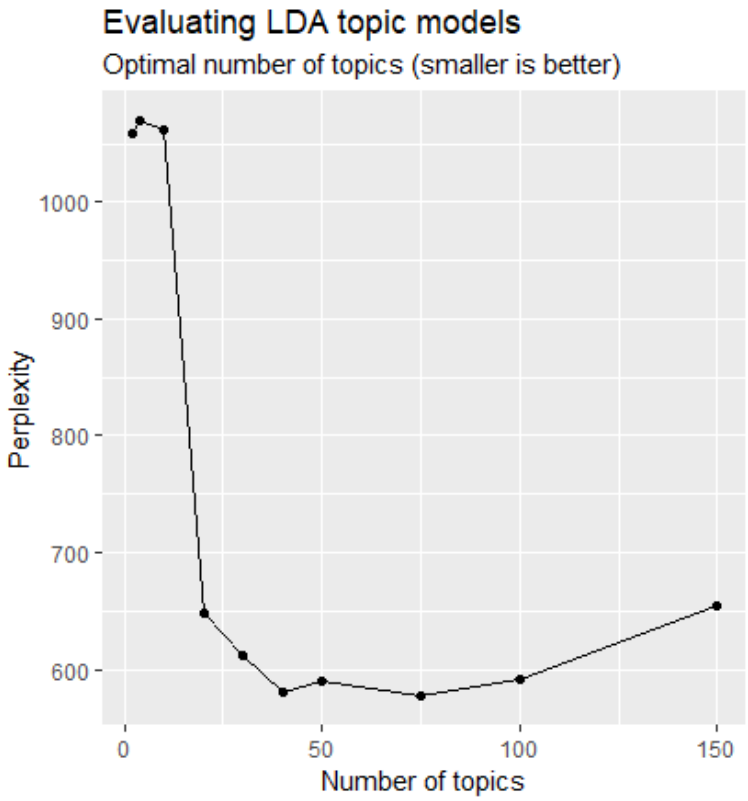
No Contact	Suspect	Prospect	Qualified	Client
		• Prospect dead • Waiting • Sent Info • Follow up • Warm • Interested	• Qualified • Hot lead • Scheduled phone appt, demo • Cancelled Appointment • Declined	• Sold

J

Total no. of Concepts Extracted from Lead Status: 36.

Word-Like	Count	Relevance
lead	194	100%
appointment	147	76%
sold	126	65%
email	119	61%
sent	115	59%
contact	110	57%
info	88	45%
interested	82	42%
appt	80	41%
follow	77	40%
pending	77	40%
dead	76	39%
needs	72	37%
scheduled	70	36%
client	70	36%
customer	63	32%
qualified	53	27%
mail	52	27%
interest	46	24%
send	45	23%
closed	45	23%
completed	45	23%
hot	44	23%
complete	41	21%
waiting	39	20%
training	38	20%
phone	38	20%
admin	38	20%
warm	34	18%
declined	34	18%
request	33	17%
cancelled	32	16%
decision	31	16%
demo	30	15%
card	29	15%
prospect	29	15%

K


Evaluating LDA topic models
Optimal number of topics (smaller is better)
Perplexity
1000
900
800
700
600
0
50
100
150
Number of topics

L

Lead Status: Identification of the Stages using LDA in R

No Contact	Suspect	Prospect	Qualified	Client
	• Denied • Refuse • Current • Do not contact • Cold	• Dead • Cancel • Prospect • Progress • Decision maker • Pending • Warm • Potential • Interest • Drip • Send info • Confirmed • Verified • Waiting	• Appointment set • Booked webinar • Quote requested • Transfer • Hot • Decline • Proposal • Registered • Lost • Pitch	• Sold • Retained • Sale • Won

M

topic	term	beta
1	appointment	0.417143
1	set	0.254286
1	working	0.057143
1	show	0.031429
1	sold:	0.025714
2	booked	0.088598
2	intro	0.059065
2	webinar	0.054847
2	fees	0.04219
2	dead-	0.037971
2	register	0.037971
3	future	0.109756
3	needed	0.105691
3	life	0.065041
3	number	0.04878
3	cancel	0.044715
4	attempt	0.091256
4	already	0.087454
4	bad	0.068442
4	pas	0.04943
4	web	0.038023
4	business	0.038023
5	per	0.11245
5	prospect	0.108434
5	denied:	0.108434
5	notification	0.060241
5	low	0.044177
6	non	0.110616
6	made	0.075219
6	lead:	0.070795
6	initial	0.048671
6	past	0.048671
7	call	0.503191
7	application	0.057691
7	post	0.044871
7	progress:	0.041665

7	please	0.03205
8	quote	0.113821
8	requested	0.089431
8	account	0.089431
8	step	0.065041
8	unable	0.04878
9	transfer	0.139237
9	data	0.06329
9	android	0.042193
9	stage	0.037974
9	live	0.033754
10	sold	0.326284
10	decision	0.093656
10	left	0.066465
10	maker	0.063444
10	message	0.048338
11	contact	0.527919
11	corp.	0.06599
11	week	0.030457
11	worth	0.020305
11	apt	0.020305
11	next	0.020305
11	rendez	0.020305
11	vous	0.020305
12	mail	0.20749
12	review	0.087146
12	cita	0.087146
12	positivo	0.041498
12	never	0.037348
12	con	0.037348
13	complete	0.138462
13	prev-mix	0.061539
13	rdv	0.057692
13	enrolled	0.046154
13	date	0.038462
13	refus	0.038462
14	fbso	0.177686
14	mix	0.107438
14	will	0.099174
14	available	0.03719
14	rep	0.028926

15	pending	0.242424
15	new	0.158249
15	hot	0.138047
15	order	0.087542
15	user	0.074074
16	cancelled	0.12971
16	hours	0.087868
16	retained	0.075316
16	update	0.046026
16	potential	0.041842
17	phone	0.139996
17	warm	0.115997
17	interview	0.083998
17	failed	0.043999
17	first	0.039999
17	fax	0.039999
18	(admin)	0.11194
18	contract	0.100746
18	offer	0.078358
18	days	0.05597
18	accepted	0.048507
19	interest	0.163636
19	deliverable	0.138182
19	vendor	0.069091
19	year	0.065455
19	visit	0.043636
20	qualified	0.199225
20	received	0.109378
20	sale	0.101565
20	test	0.054689
20	credit	0.046876
21	degree	0.077135
21	ready	0.064279
21	voicemail	0.042853
21	decline	0.034282
21	associate	0.034282
21	close	0.034282
21	existing	0.034282
22	prev-	0.238427
22	customer	0.224193
22	yes	0.085407

22	letter	0.021352
22	patient	0.017793
23	email	0.419802
23	drip	0.068695
23	online	0.057246
23	pay	0.04198
23	doa	0.038164
24	appt	0.259935
24	sales	0.122747
24	demo	0.104696
24	proposal	0.068594
24	person	0.057763
25	info	0.369099
25	send	0.193133
25	final	0.042918
25	leads	0.038627
25	consult	0.025751
25	pass	0.025751
26	confirmed	0.110204
26	information	0.073469
26	completed:	0.053061
26	schedule	0.028571
26	verified	0.028571
27	client	0.283269
27	closed	0.180262
27	yet	0.04292
27	approval	0.038628
27	won	0.034336
27	account,	0.034336
28	waiting	0.143382
28	completed	0.106618
28	active	0.091912
28	signed	0.051471
28	docs	0.044118
28	survey	0.044118
28	current	0.044118
28	registered	0.044118
29	training	0.142292
29	request	0.130435
29	card	0.114625
29	comm	0.075099

29	ordered	0.031621
29	cards	0.031621
30	dead	0.22008
30	declined	0.119692
30	app	0.061777
30	payment	0.054055
30	process	0.050194
31	sent	0.442687
31	time	0.079051
31	approved	0.055336
31	updated	0.055336
31	office	0.031621
32	line	0.230769
32	exp	0.174089
32	registration	0.044534
32	required	0.040486
32	dnc	0.036437
33	interested	0.305344
33	back	0.137405
33	aca	0.087786
33	plan	0.045802
33	quoted	0.034351
34	follow	0.300781
34	service	0.058594
34	program	0.054687
34	month	0.046875
34	follow-	0.035156
35	cold	0.120332
35	meeting	0.107884
35	reached	0.095436
35	wants	0.062241
35	wip	0.045643
36	need	0.106869
36	reschedule	0.079162
36	lost	0.047497
36	verification	0.047497
36	ach	0.043539
37	needs	0.235528
37	company	0.101458
37	hotel	0.094211
37	area.	0.043482

37	area	0.036235
38	scheduled	0.264591
38	callback	0.11284
38	contacted	0.085603
38	open	0.054475
38	group	0.035019
39	lead	0.519187
39	rescheduled	0.058999
39	health	0.044249
39	unworkable	0.038349
39	2nd	0.026549
39	pitch	0.026549

N

Qualification Ratio Classes

[0,0.1853933]	(0.1853933,0.6086957]	(0.6086957,1]
Low	Medium	High

Prospect Ratio Classes

[0,0.2361111]	(0.2361111,0.6513317]	(0.6513317,1]
Low	Medium	High

Suspect Ratio Classes

[0,0.3248945]	(0.3248945,0.6308594]	(0.6308594,1]
Low	Medium	High

O

***Solitary Leads Highlighted in Yellow**

No Contact	436,891
No Contact + Suspect	156,134
Suspect	152,783
No Contact+Prospect	106,695
Prospect	22,354
No Contact + Suspect +Prospect	19,483
No Contact+Qualified	12,183
Qualified	9,750
Suspect+Prospect	5,914
No Contact+Prospect+Qualified	2,783
No Contact+Suspect+Qualified	1,748
Prospect+Qualified	1,013
No Contact + Suspect +Prospect+Qualified	884
Suspect+Qualified	255
No Contact + Client	107
No Contact+ Prospect + Client	103
Prospect + Client	92
Client	90
No Contact + Suspect+ Client	82
Suspect + Prospect + Qualified	57
No Contact + Suspect + Prospect +Client	17
Suspect+ Qualified	17
No Contact + Prospect + Qualified + Client	13
Prospect + Qualified + Client	12
No Contact + Qualified + Client	10
Qualified + Client	9
No Contact + Suspect + Qualified + Client	1
No Contact + Suspect + Prospect + Qualified + Client	1

Total Leads	929,481
Progressed Leads=Total Leads -No Contact	492,590

Solitary Leads	460,096
Percentage of Progressed Leads that are Solitary Leads	93%

P

Coefficients[a]

Model		Correlations			Collinearity Statistics	
		Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)					
	TeamSizeSus	.185	-.037	-.036	.158	6.310
	TeamExperienceSus	-.044	-.027	-.026	.913	1.095
	TeamEffortSus	.236	.136	.132	.357	2.800
	TaskInputSus	.085	-.017	-.016	.311	3.215
	TeamGoalMonitoringSus	.076	-.046	-.044	.586	1.707
	SpecificityofRoleSus	-.048	-.059	-.057	.958	1.044
	RepetitionSus	.050	.028	.027	.907	1.103
	Intra-TeamCommunicationSus	.198	.065	.063	.140	7.135

Coefficients[a]

Model		Correlations			Collinearity Statistics	
		Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)					
	TeamSizePros	.288	-.179	-.135	.182	5.510

	TeamExperiencePros	-.003	.034	.025	.912	1.096
	TeamEffortPros	.247	.020	.015	.373	2.678
	TaskInputPros	.295	-.151	-.114	.234	4.267
	TeamGoalMonitoringPros	.561	.345	.273	.546	1.832
	SpecificityofRolePros	-.046	-.056	-.042	.939	1.064
	RepetitionPros	.119	.016	.012	.779	1.283
	Intra-TeamCommunicationPros	.559	.335	.264	.143	7.011

Coefficients[a]

		Correlations			Collinearity Statistics	
Model		Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)					
	TeamSizeQual	-.085	-.243	-.203	.184	5.433
	TeamExperienceQual	.197	.125	.102	.867	1.153
	TeamEffortQual	.087	.270	.227	.401	2.491
	TaskInputQual	.493	.104	.084	.200	5.004
	TeamGoalMonitoringQual	-.040	.101	.082	.555	1.801
	SpecificityofRoleQual	-.112	-.088	-.071	.955	1.047
	RepetitionQual	-.136	-.074	-.060	.810	1.235
	Intra-TeamCommunicationQual	.425	.178	.146	.173	5.777

Q

Likelihood Ratio Tests

Effect	Model Fitting Criteria: AIC of Reduced Model	Model Fitting Criteria: BIC of Reduced Model	Model Fitting Criteria: -2 Log Likelihood of Reduced Model	Likelihood Ratio: Chi-Square
Intercept	6822.055	6946.570	6782.055[a]	.000
TeamSizeSus	6857.110	6969.174	6821.110	39.055
TeamExperienceSus	6822.710	6934.774	6786.710	4.655
TeamEffortSus	6933.438	7045.502	6897.438	115.383
TaskInputSus	6828.433	6940.497	6792.433	10.378
TeamGoalMonitoringSus	6830.232	6942.296	6794.232	12.177
SpecificityofRoleSus	6827.954	6940.018	6791.954	9.899
RepetitionSus	6898.479	7010.543	6862.479	80.425
Intra-TeamCommunicationSus	6855.156	6967.220	6819.156	37.101
Industry	6822.382	6934.446	6786.382	4.327

Likelihood Ratio Tests

Effect	Model Fitting Criteria: AIC of Reduced Model	Model Fitting Criteria: BIC of Reduced Model	Model Fitting Criteria: -2 Log Likelihood of Reduced Model	Likelihood Ratio: Chi-Square

Intercept	1741.273	1855.762	1701.273[a]	.000	0
TeamSizePros	1860.521	1963.561	1824.521	123.248	2
TeamExperiencePros	1759.150	1862.190	1723.150	21.877	2
TeamEffortPros	1799.577	1902.617	1763.577	62.304	2
TaskInputPros	1803.697	1906.737	1767.697	66.424	2
TeamGoalMonitoringPros	2068.985	2172.025	2032.985	331.712	2
SpecificityofRolePros	1746.863	1849.903	1710.863	9.590	2
RepetitionPros	1788.207	1891.247	1752.207	50.934	2
Intra-TeamCommunicationPros	1955.657	2058.697	1919.657	218.384	2
Industry	1739.863	1842.903	1703.863	2.590	2

Likelihood Ratio Tests

	Model Fitting Criteria			Likelihood Ratio
Effect	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square
Intercept	1572.790	1682.274	1532.790[a]	.000
TeamSizeQual	1633.514	1732.050	1597.514	64.725
TeamExperienceQual	1599.944	1698.480	1563.944	31.154
TeamEffortQual	1625.855	1724.391	1589.855	57.065
TaskInputQual	1584.657	1683.192	1548.657	15.867
TeamGoalMonitoringQual	1601.367	1699.902	1565.367	32.577
SpecificityofRoleQual	1574.366	1672.902	1538.366	5.576
RepetitionQual	1587.621	1686.157	1551.621	18.832
Intra-TeamCommunicationQual	1615.215	1713.751	1579.215	46.425

Industry	1569.212	1667.747	1533.212	.422	2

R

Case Processing Summary

		N	Marginal Percentage
Suspect Ratio	1	1337	35.8%
	2	1857	49.7%
	3	542	14.5%
Industry	Insurance	10	0.3%
	Marketing and Advertising	3726	99.7%
Valid		3736	100.0%
Missing		360	
Total		4096	
Subpopulation		3734[a]	

a. The dependent variable has only one value observed in 3734 (100.0%) subpopulations.

Model Fitting Information

	Model Fitting Criteria			Likelihood Ratio Tests		
Model	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	7440.719	7453.171	7436.719			

Final	6822.055	6946.570	6782.055	654.664	18	.000

Pseudo R-Square

Cox and Snell	.161
Nagelkerke	.186
McFadden	.088

Likelihood Ratio Tests

	Likelihood Ratio Tests
Effect	Sig.
Intercept	.
TeamSizeSus	.000
TeamExperienceSus	.098
TeamEffortSus	.000
TaskInputSus	.006
TeamGoalMonitoringSus	.002
SpecificityofRoleSus	.007
RepetitionSus	.000
Intra-TeamCommunicationSus	.000
Industry	.115

Parameter Estimates

Suspect Ratio[a]		B	Std. Error	Wald	df	Sig.	Exp(B)
2	Intercept	2.050	1.218	2.832	1	.092	
	TeamSizeSus	.125	.058	4.599	1	.032	1.133
	TeamExperienceSus	-.002	.004	.296	1	.586	.998
	TeamEffortSus	.237	.048	24.601	1	.000	1.268
	TaskInputSus	-.026	.029	.776	1	.378	.974
	TeamGoalMonitoringSus	-.097	.087	1.240	1	.265	.907
	SpecificityofRoleSus	-3.300	1.170	7.957	1	.005	.037
	RepetitionSus	.133	.016	66.247	1	.000	1.142
	Intra-TeamCommunicationSus	.038	.019	3.776	1	.052	1.039
	[Industry=Insurance]	-1.456	1.154	1.593	1	.207	.233
	[Industry=Marketing and Advertising]	0[b]	.	.	0	.	.
3	Intercept	1.366	1.571	.756	1	.385	
	TeamSizeSus	-.243	.074	10.807	1	.001	.784
	TeamExperienceSus	-.012	.005	4.531	1	.033	.988
	TeamEffortSus	.550	.055	100.618	1	.000	1.733
	TaskInputSus	-.122	.040	9.129	1	.003	.886
	TeamGoalMonitoringSus	-.402	.118	11.685	1	.001	.669
	SpecificityofRoleSus	-2.804	1.500	3.494	1	.062	.061
	RepetitionSus	.078	.022	12.577	1	.000	1.081

	Intra-TeamCommunicationSus	.135	.024	31.087	1	.000	1.145
	[Industry=Insurance]	.294	1.129	.068	1	.794	1.342
	[Industry=Marketing and Advertising]	0[b]	.	.	0	.	.

S

Case Processing Summary

		N	Marginal Percentage
Prospect Ratio	1	1658	73.3%
	2	403	17.8%
	3	202	8.9%
Industry	Insurance	9	0.4%
	Marketing and Advertising	2254	99.6%
Valid		2263	100.0%
Missing		1888	
Total		4151	
Subpopulation		2260[a]	

Model Fitting Information

	Model Fitting Criteria			Likelihood Ratio Tests		
Model	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.

Intercept Only	3402.436	3413.885	3398.436			
Final	1741.273	1855.762	1701.273	1697.164	18	.000

Pseudo R-Square

Cox and Snell	.528
Nagelkerke	.679
McFadden	.499

Likelihood Ratio Tests

Effect	Likelihood Ratio Tests Sig.
Intercept	.
TeamSizePros	.000
TeamExperiencePros	.000
TeamEffortPros	.000
TaskInputPros	.000
TeamGoalMonitoringPros	.000
SpecificityofRolePros	.008
RepetitionPros	.000
Intra-TeamCommunicationPros	.000
Industry	.274

Parameter Estimates

Prospect Ratio[a]		B	Std. Error	Wald	df	Sig.	Exp(B)
2	Intercept	1.922	1.619	1.409	1	.235	
	TeamSizePros	-.928	.097	90.743	1	.000	.395
	TeamExperiencePros	.003	.009	.113	1	.737	1.003
	TeamEffortPros	.283	.044	40.717	1	.000	1.327
	TaskInputPros	-.168	.033	26.335	1	.000	.845
	TeamGoalMonitoringPros	3.214	.266	145.695	1	.000	24.875
	SpecificityofRolePros	-5.608	1.593	12.396	1	.000	.004
	RepetitionPros	.140	.025	31.110	1	.000	1.150
	Intra-TeamCommunicationPros	.217	.022	99.294	1	.000	1.243
	[Industry=Insurance]	2.426	1.247	3.787	1	.052	11.313
	[Industry=Marketing and Advertising]	0[b]	.	.	0	.	.
3	Intercept	-1.753	2.238	.614	1	.433	
	TeamSizePros	-.995	.128	60.258	1	.000	.370
	TeamExperiencePros	.057	.013	18.697	1	.000	1.059
	TeamEffortPros	-.185	.097	3.629	1	.057	.831
	TaskInputPros	-.331	.044	55.836	1	.000	.718
	TeamGoalMonitoringPros	3.772	.299	159.247	1	.000	43.459
	SpecificityofRolePros	-3.971	2.127	3.485	1	.062	.019
	RepetitionPros	.019	.037	.272	1	.602	1.019
	Intra-TeamCommunicationPros	.338	.028	141.913	1	.000	1.403
	[Industry=Insurance]	-14.529	.000	.	1	.	4.898E-7
	[Industry=Marketing and Advertising]	0[b]	.	.	0	.	.

T

Case Processing Summary

		N	Marginal Percentage
Qualification Ratio	1	1345	76.3%
	2	310	17.6%
	3	107	6.1%
Industry	Insurance	9	0.5%
	Marketing and Advertising	1753	99.5%
Valid		1762	100.0%
Missing		2358	
Total		4120	
Subpopulation		1760[a]	

Model Fitting Information

	Model Fitting Criteria			Likelihood Ratio Tests		
Model	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2407.276	2418.224	2403.276			
Final	1572.790	1682.274	1532.790	870.486	18	.000

Pseudo R-Square

Cox and Snell	.390
Nagelkerke	.524
McFadden	.362

Likelihood Ratio Tests

Effect	Likelihood Ratio Tests Sig.
Intercept	.
TeamSizeQual	.000
TeamExperienceQual	.000
TeamEffortQual	.000
TaskInputQual	.000
TeamGoalMonitoringQual	.000
SpecificityofRoleQual	.062
RepetitionQual	.000
Intra-TeamCommunicationQual	.000
Industry	.810

Parameter Estimates

Qualification Ratio[a]		B	Std. Error	Wald	df	Sig.	Exp(B)
2	Intercept	-.197	1.775	.012	1	.911	
	TeamSizeQual	-.448	.076	34.760	1	.000	.639
	TeamExperienceQual	.037	.008	23.974	1	.000	1.038
	TeamEffortQual	.325	.043	58.196	1	.000	1.384
	TaskInputQual	.120	.031	15.415	1	.000	1.128
	TeamGoalMonitoringQual	.191	.100	3.630	1	.057	1.210
	SpecificityofRoleQual	-4.018	1.717	5.476	1	.019	.018
	RepetitionQual	-.163	.053	9.311	1	.002	.850

	Intra-TeamCommunicationQual	.107	.020	29.378	1	.000	1.113
	[Industry=Insurance]	-.517	.960	.290	1	.590	.596
	[Industry=Marketing and Advertising]	0[b]	.	.	0	.	.
3	Intercept	-.819	2.292	.128	1	.721	
	TeamSizeQual	-1.019	.169	36.355	1	.000	.361
	TeamExperienceQual	.051	.012	17.837	1	.000	1.052
	TeamEffortQual	.249	.083	9.031	1	.003	1.283
	TaskInputQual	.096	.038	6.304	1	.012	1.101
	TeamGoalMonitoringQual	.941	.154	37.095	1	.000	2.562
	SpecificityofRoleQual	-3.684	2.113	3.039	1	.081	.025
	RepetitionQual	-.362	.142	6.513	1	.011	.696
	Intra-TeamCommunicationQual	.166	.027	37.024	1	.000	1.181
	[Industry=Insurance]	.106	1.418	.006	1	.941	1.112
	[Industry=Marketing and Advertising]	0[b]	.	.	0	.	.

U

Case Processing Summary

Suspect Ratio	Valid N (listwise)
Positive[a]	1857
Negative	1879
Missing	360

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. The positive actual state is 2.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
TeamSizeSus	.628	.009	.000	.610	.646
TeamExperienceSus	.491	.009	.323	.472	.509
TeamEffortSus	.607	.009	.000	.589	.625
TaskInputSus	.495	.009	.608	.477	.514
TeamGoalMonitoringSus	.543	.009	.000	.524	.561
SpecificityofRoleSus	.478	.009	.022	.460	.497
RepetitionSus	.624	.009	.000	.606	.642
Intra-TeamCommunicationSus	.579	.009	.000	.560	.597

Case Processing Summary

Suspect Ratio	Valid N (listwise)

Positive[a]	542
Negative	3194
Missing	360

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. The positive actual state is 3.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
TeamSizeSus	.622	.012	.000	.599	.646
TeamExperienceSus	.463	.014	.006	.437	.489
TeamEffortSus	.676	.012	.000	.653	.699
TaskInputSus	.584	.014	.000	.557	.612
TeamGoalMonitoringSus	.530	.014	.023	.503	.558
SpecificityofRoleSus	.503	.014	.837	.476	.530
RepetitionSus	.451	.014	.000	.423	.480
Intra-TeamCommunicationSus	.663	.012	.000	.639	.687

Case Processing Summary

Prospect Ratio	Valid N (listwise)
Positive[a]	403
Negative	1860

Missing	1888

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. The positive actual state is 2.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
TeamSizePros	.667	.014	.000	.639	.694
TeamExperiencePros	.454	.017	.004	.421	.486
TeamEffortPros	.691	.012	.000	.667	.715
TaskInputPros	.660	.013	.000	.634	.686
TeamGoalMonitoringPros	.822	.011	.000	.799	.844
SpecificityofRolePros	.474	.017	.103	.440	.508
RepetitionPros	.685	.016	.000	.654	.715
Intra-TeamCommunicationPros	.795	.011	.000	.774	.817

Case Processing Summary

Prospect Ratio	Valid N (listwise)
Positive[a]	202
Negative	2061
Missing	1888

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. The positive actual state is 3.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
TeamSizePros	.631	.021	.000	.590	.672
TeamExperiencePros	.533	.023	.117	.489	.578
TeamEffortPros	.638	.018	.000	.603	.673
TaskInputPros	.739	.017	.000	.707	.771
TeamGoalMonitoringPros	.885	.010	.000	.865	.905
SpecificityofRolePros	.443	.021	.008	.402	.484
RepetitionPros	.597	.020	.000	.558	.636
Intra-TeamCommunicationPros	.830	.016	.000	.800	.861

Case Processing Summary

Qualification Ratio	Valid N (listwise)
Positive[a]	310
Negative	1452
Missing	2358

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. The positive actual state is 2.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
TeamSizeQual	.478	.016	.228	.447	.509
TeamExperienceQual	.619	.018	.000	.584	.653
TeamEffortQual	.604	.016	.000	.574	.635
TaskInputQual	.825	.012	.000	.801	.849
TeamGoalMonitoringQual	.443	.018	.002	.409	.478
SpecificityofRoleQual	.456	.017	.014	.422	.489
RepetitionQual	.370	.015	.000	.340	.399
Intra-TeamCommunicationQual	.732	.015	.000	.703	.761

Case Processing Summary

Qualification Ratio	Valid N (listwise)
Positive[a]	107
Negative	1655
Missing	2358

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. The positive actual state is 3.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval

				Lower Bound	Upper Bound
TeamSizeQual	.338	.022	.000	.295	.381
TeamExperienceQual	.715	.024	.000	.668	.762
TeamEffortQual	.465	.024	.221	.417	.513
TaskInputQual	.810	.025	.000	.762	.859
TeamGoalMonitoringQual	.542	.026	.141	.491	.593
SpecificityofRoleQual	.446	.026	.059	.394	.497
RepetitionQual	.222	.024	.000	.175	.268
Intra-TeamCommunicationQual	.714	.029	.000	.657	.770

V

Bootstrap for Parameter Estimates

Suspect Ratio		B	Bootstrap[a] Bias	Bootstrap[a] Std. Error	Bootstrap[a] Sig. (2-tailed)
2	Intercept	2.035	.102	1.244	.076
	TeamSizeSus	.125	.004	.065	.059
	TeamExperienceSus	-.002	.000	.004	.578
	TeamEffortSus	.237	-.001	.052	.001
	TaskInputSus	-.026	-.001	.033	.424
	TeamGoalMonitoringSus	-.099	-.003	.091	.273
	SpecificityofRoleSus	-3.285	-.107	1.191	.003
	RepetitionSus	.133	.001	.019	.001
	Intra-TeamCommunicationSus	.038	.000	.022	.085
	[Industry=Insurance]	-1.454	1560.037	46437.722	.215
	[Industry=Marketing and Advertising]	0	0	0	
3	Intercept	1.351	.128	1.384	.294
	TeamSizeSus	-.243	.001	.076	.001
	TeamExperienceSus	-.012	.000	.006	.037
	TeamEffortSus	.550	.001	.057	.001
	TaskInputSus	-.122	-.001	.043	.006
	TeamGoalMonitoringSus	-.403	.005	.122	.001
	SpecificityofRoleSus	-2.789	-.136	1.315	.020
	RepetitionSus	.078	-.001	.026	.005

	Intra-TeamCommunicationSus	.135	.001	.026	.001
	[Industry=Insurance]	.296	2.376	7.109	.774
	[Industry=Marketing and Advertising]	0	0	0	

Bootstrap for Parameter Estimates

Prospect Ratio		B	Bootstrap[a] Bias	Std. Error	Sig. (2-tailed)
2	Intercept	1.997	.882[b]	2.629[b]	.186[b]
	TeamSizePros	-.922	-.018[b]	.121[b]	.001[b]
	TeamExperiencePros	.003	.000[b]	.009[b]	.697[b]
	TeamEffortPros	.273	.006[b]	.044[b]	.001[b]
	TaskInputPros	-.170	-.005[b]	.043[b]	.001[b]
	TeamGoalMonitoringPros	2.938	.072[b]	.406[b]	.001[b]
	SpecificityofRolePros	-5.432	-.949[b]	2.549[b]	.010[b]
	RepetitionPros	.149	.002[b]	.024[b]	.001[b]
	Intra-TeamCommunicationPros	.220	.005[b]	.031[b]	.001[b]
	[Industry=Insurance]	2.235	-6.106[b]	9.037[b]	.070[b]
	[Industry=Marketing and Advertising]	0	0[b]	0[b]	
3	Intercept	-1.597	1.005[b]	2.764[b]	.417[b]
	TeamSizePros	-.986	-.027[b]	.136[b]	.001[b]
	TeamExperiencePros	.058	.001[b]	.011[b]	.001[b]
	TeamEffortPros	-.198	-.003[b]	.097[b]	.046[b]

	TaskInputPros	-.334	-.013[b]	.049[b]	.001[b]
	TeamGoalMonitoringPros	3.473	.080[b]	.414[b]	.001[b]
	SpecificityofRolePros	-3.851	-1.012[b]	2.648[b]	.070[b]
	RepetitionPros	.029	-.004[b]	.034[b]	.394[b]
	Intra-TeamCommunicationPros	.342	.009[b]	.035[b]	.001[b]
	[Industry=Insurance]	-14.813	.297[b]	.843[b]	
	[Industry=Marketing and Advertising]	0	0[b]	0[b]	

Bootstrap for Parameter Estimates

			Bootstrap[a]		
Qualification Ratio		B	Bias	Std. Error	Sig. (2-tailed)
2	Intercept	-.140	.161[b]	1.686[b]	.919[b]
	TeamSizeQual	-.455	-.011[b]	.089[b]	.001[b]
	TeamExperienceQual	.036	.001[b]	.007[b]	.001[b]
	TeamEffortQual	.325	.004[b]	.044[b]	.001[b]
	TaskInputQual	.118	.000[b]	.042[b]	.004[b]
	TeamGoalMonitoringQual	.205	.001[b]	.110[b]	.056[b]
	SpecificityofRoleQual	-4.020	-.179[b]	1.600[b]	.007[b]
	RepetitionQual	-.161	-.010[b]	.057[b]	.005[b]
	Intra-TeamCommunicationQual	.108	.002[b]	.026[b]	.001[b]
	[Industry=Insurance]	-.514	18.773[b]	632.682[b]	.556[b]
	[Industry=Marketing and Advertising]	0	0[b]	0[b]	

3	Intercept	-.690	.141[b]	2.085[b]	.685[b]
	TeamSizeQual	-1.039	-.041[b]	.186[b]	.001[b]
	TeamExperienceQual	.050	-.001[b]	.011[b]	.001[b]
	TeamEffortQual	.248	.001[b]	.080[b]	.004[b]
	TaskInputQual	.091	-.004[b]	.048[b]	.051[b]
	TeamGoalMonitoringQual	.946	.032[b]	.158[b]	.001[b]
	SpecificityofRoleQual	-3.698	.008[b]	1.963[b]	.025[b]
	RepetitionQual	-.362	-.063[b]	.265[b]	.104[b]
	Intra-TeamCommunicationQual	.170	.005[b]	.033[b]	.001[b]
	[Industry=Insurance]	.125	-1.963[b]	113.113[b]	.917[b]
	[Industry=Marketing and Advertising]	0	0[b]	0[b]	