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Aspects of eCRM and firmographics that influence customer acquisition probability

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Abstract

The goal of this master thesis is to study which aspects of eCRM and firmographics increase the customer acquisition likelihood. The data that has been gathered was provided to the researcher by the company and consists of N= 124 408 observations. The novelty of this research is in the context of studying specific eCRM components such as content relevance and message format (which is to be defined as a set of ideal characteristics of a message which lead to different behavioral outcomes), as well as different firmographics such as company size, company industry, job title, and geographic location of prospects and its impact on customer acquisition probability. Furthermore, this research provides precise recommendations to the entity regarding their outbound sales process and provides recommendations to all companies in general which may be interested in expanding their outbound efforts by segmenting each of the eCRM and firmographic components further and provide recommendations accordingly. This research uses quantitative research methods by making use of logistic regression and linear discriminant analysis and cross-examines both in order to verify the results. The added value of the study as observed is that the two aspects of eCRM that were examined were considered the worse predictors of the model, however, the firmographics did contribute to a great extent in increasing the customer acquisition probability. Out of the two aspects of eCRM examined, it was proven that content relevance has more influence over customer acquisition probability compared to message format.

1 Introduction

There is no doubt that the successful customer relationship management strategies have the capacity to improve the performance of the firm from a managerial perspective in areas such as customer development, customer retention and customer acquisition (Nichita, Vulpoi, & Toader, 2013). Becker, Greve, & Albers (2009) also state that the three most important objective of the CRM are customer acquisition, customer maintenance, and customer retention (Pozza, Goetz, & Sahut, 2018). Therefore, it seems that both views are aligned on the fact that one of the most important objectives in having an efficient CRM strategy is to have a proper customer acquisition process.

The eCRM is an extension of the traditional CRM and it concerns all forms of managing connections with customers by making use of information technology (Singh & Saini, 2016). However, by taking into consideration the fact that the current communication and information technologies enable businesses to foster from the customer relation in a far more efficient and effective way, the eCRM as an extension of the old traditional CRM, proves to be more suitable instrument/method, due to the innovative era in which the businesses are allocated nowadays when compared to the old traditional CRM by its own (Shoniregun et al., 2004). We can the conclude that CRM and the eCRM are interrelated, but still different. It is important to note that Sign & Saini (2016) and (Shoniregun et al., 2004) have the same opinion when it comes to the definition of the eCRM as both articles view the eCRM as an extension of the traditional CRM approach and both articles identify that the eCRM improves the customer base, market share of the companies, bulk purchase, promote product image, identify customer needs, and contribute to fast and reliable business transactions.

Nevertheless, when acquiring new customers, a large number of companies face high uncertainty in the customer responses within their promotional campaigns which are done online (Liu, Pancras, & Houtz, 2014). This is particularly relevant for the so-called direct marketing, in which the salespeople/ marketeers of companies are limited in the number of people to whom they can reach on a daily basis. Therefore, the right customer targeting in the customer acquisition process is essential which results in more effective communication and higher customer acquisition (Migueis, Camanho, & Borges, 2017).

The current literature gap was identified by looking at (Pozza, Goetz, & Sahut, 2018; Osarenkhoe & Bennani, 2007; Richards & Jones, 2008; Landry, Todd, & Arndt, 2005; Moutot & Bascoul, 2008).

Firstly, Pozza, Goetz, & Sahut (2018) describe advances the research on the CRM field by investigating the impact of the relation time implementation according to which the interventions are implemented in different areas such as CRM technology, customer management, organizational alignment as well as CRM strategy on the CRM performance indicator. The overall results indicated that the CRM implantations do not equally address the areas of customer acquisition. Further to that the CRM implementations do not equally address other areas such as loyalty, growth, as the company objectives and the geographical differences are crucial and are more important independent variables.

Secondly, Osarenkho & Bennani (2007) show that the CRM is not just a tactical weapon, but also represents a different strategic approach when looking at buyer-seller exchanges. The findings of the article of Osarenkho & Bennani (2007) showed that implementing sustainable CRM strategy requires the endorsement of the top management. The practical implications of the research indicated that the CRM is a strategic business and process issue, which is not merely a technology solution due to the fact that most often conceived in practice.

Thirdly, Richards & Jones (2008) have demonstrated what is the relationship of different CRM value drivers such as targeting profitable customers, integrating offerings across channels, improving sales force efficiency and effectiveness, improving pricing, customize products and services, improve customer services effectiveness and efficiency, and having an individualized marketing message on the customer equity variable.

Next, Landry, Todd, & Arndt (2005) research the role of information technology in the customer relationship management field. They do that by looking at the two main sales forces that exist out there, namely the firm and the customer and the relationship between them. On the one hand, they describe that CRM technologies such as self-service technologies, one-to-one internet marketing, and logistic information systems are the ones that are used by the firms in their interaction with the customers. On the other hand, the CRM technologies that are used by the customers in their interaction with the firms are CRM technologies such as EDI, vendor managed inventories, continuous planning forecasting, and automated replenishment.

Finally, Moutot & Bascoul (2008) analyze the effect of salesforce automation use on sales force activities and customer relationship management. They studied this relationship by looking at it from the perspective of information systems as well as motivation theories. The paper came up with two alternative models that distinguish the effectiveness and efficient of salesperson’s activities. The data from a longitudinal field demonstrated that the different SFA functionalities are able to generate effects on sales activities which were counterintuitive at first place. The findings suggest the SFA implementation in the CRM processes have a negative effect of SFA reporting and conflicting, however, are complementary and globally positively affecting the SFA product and planning configuration.

From this overview, we can see that all the articles pay close attention to the relation between the traditional CRM and customer acquisition and optimization of sales and marketing processes in general terms.

However, there are no articles published so far found in the literature that try to analyze the effect aspects of eCRM acquisition strategy that have an influence on the customer acquisition probability on customer acquisition by taking into consideration the predictor variables that increase the probability of customer acquisition which in this case will be the theoretical contribution of this paper. The practical contribution of the researcher in this case lies in the fact that he will potentially be bringing new customers to the entity while conducting the research and will be growing his own data base for the quantitative analysis by which he will give insight to the entity about the predictor variables that they will have to take into account in their outbound sales approach.

Therefore, the importance of constructing a clear acquisition strategy in the business literature follows from the fact that a good acquisition strategy is one of the fundamental principles of setting clear key performance indicators across companies in the globalization era that we are currently living which in return shall lead to higher customer acquisition rate (Rigby & Jones, 2008).

As a result, the following research question is brought into the table: “What aspects of eCRM acquisition strategy have an influence on acquisition probability?”

In terms of a preview, this thesis proposal consists of four main chapters. The next chapter will provide further insight on the theory that will be used in the original thesis by taking into consideration the key papers, existing theory, and the concepts that will be introduced in this paper. Furthermore, chapter 3 will give insight on the research design which will give further insight on the methods that will be used and all the necessary tools that will help us in answering the central research question. Finally, Chapter 4 on the results of this research. Chapter 5 provides insights on the overall discussion of the research, and chapter 6 provides recommendations and conclusions to the entity as well as companies in general.

2 Theory

Customer acquisition has been one of the most important bases of a good CRM strategy (Aspara, 2011). This is so, as customer acquisition as a variable has been classified by Pozza, Goetz, & Sahut, (2018) to be as a variable which is a facet of CRM performance. This section, therefore, will analyze in-depth the eCRM process of the companies as well as the customer acquisition in-depth and come up with predictor variables which strengthen the relationship.

2.1 Dimensions of eCRM and customer acquisition

There are three dimensions of the CRM which are the operational, the analytical, and the strategic CRM (Singh & Saini, 2016). Firstly, the operational CRM streamlines the process in the business which includes marketing, sales automation, and service automation. The main purpose of the operational CRM is to generate leads and convert them into contacts (Singh & Saini, 2016). Secondly, the analytical CRM supports the top management, sales and support, and the marketing personnel to determine better ways of serving their customers by making use of data analysis activities and results in supporting the top management to take better decisions (Singh & Saini, 2016). Thirdly, the strategic CRM enables organization to share customers information between various business units such as marketing team, sales team and support team in order to help them to use all information which was provided to improve the quality of customer service as well as gain loyalty and acquire new customers (Singh & Saini, 2016). By taking into consideration all the above-mentioned terms, we can conclude that the operational eCRM, the analytical eCRM, and the strategic eCRM will share the same definitions, respectively however, will also include the element of making use of the information technology component as mentioned in the first sentence of this paragraph. The scope of this thesis will be primarily limited to the operational CRM, as new businesses will be generated in order to convert them to contacts/calls and possible purchases. With that said, this thesis will be focused into the operational eCRM in order to fill in the literature gap.

Customer acquisition refers to a set of systems and methodologies for managing customer inquiries and prospects which are generated by a variety of marketing techniques. Some type of acquisition tools which companies use to strengthen their customer base include advertisements, sales, promotions, emails, referrals and many others (Singh & Saini, 2016). Pozza, Goetz, & Sahut (2018) already prove that the dimensions of the eCRM is positively related to customer acquisition as a CRM performance indicator. Therefore, we will assume that the dimension of eCRM is also positively related to the customer acquisition probability as a CRM performance indicator.

The type of acquisition tool which will be applied in this research will be email marketing (Sign & Saini, 2016).

2.2 Content relevance and Customer acquisition probability

When looking at the previous literature, it is demonstrated by Heinonen & Strandvik (2007) that the customer acquisition probability increases when consumers view information with higher content relevance as well as medium acceptance. This claim is supported also by Kumar, Jacquelyn, & Reinartz (2005) who state that higher level of bidirectional communication is associated with higher purchase frequencies and message customization enables rich interaction and allows for personal relationship building (Moriatry & Spekman, 1984; Kumar & Venkatesan, 2004). The main factors that influence the consumer's responsiveness towards marketing communication can be summarized as in figure 1 at the appendix:

Looking at the three pluses in figure 1, we can see that consumers are more likely to respond towards a certain message when have a high content relevance message delivered at the right media channel as well as at the right time. The main content delivery channels for prospecting that exist out there are search engines, e-mail, advertising media, and social media (Jarvien & Taiminen, 2016). With that being said, content relevance is defined as one of the main factors that has influence over the consumer responsiveness within content delivery channels such as e-mails, social media, advertising media, and search engines (Heinonen & Strandvik ,2007; Jarvien & Taiminen, 2016). This thesis will not be able to test all of the channels due to the fact that we are dealing with a cross-sectional approach and will therefore use the e-mail marketing channel. The overall marketing and sales funnel can be summarized in figure 2 in the appendix.

The content relevance is therefore crucial for the marketing operations part of the companies which consist of the first two stages, namely identifying the right contacts and generating marketing leads as it increases the customer acquisition probability by moving it to stage three until stage five.

It is stated by Sahni, Wheeler & Chintagunta (2018) that personalization and content relevance increase the customer acquisition probability as the content becomes more relevant from the perspective of the potential prospect. One way of personalizing and making the content more relevant is to state how the product/service that is being sold solves pain points that the customer recognizes for companies that are in similar sectors or are competitors. As a result, the following hypothesis is being predicted:

H1: A message with high content relevance from the perspective of the customer increases the customer acquisition probability.

Given this hypothesis, this paper predicts based on the theoretical support that the more relevant the content is for the companies towards which the messages are being sent, the higher the chance that they convert to paying customers.

2.3 Message format and Customer acquisition probability

Buyer purchase decisions substantial research attention in the today's literature (Epp & Price, 2008; Gupta, Hagerty & Myers, 1983). The typical decision-making roles can be classified in several categories, namely disposers, users, deciders, buyers, gatekeepers, and influencers (Kumar & Reinartz, 2016). One of the main questions that marketeers need to answer, according to Kumar & Reinartz (2016) is to understand how the marketing strategy of the salespeople/marketeers needs to be designed so that the right influencers of the potential buyers are reached out with the right message format and right time.

When we look at the current literature, we will also find that the different message formats are effective in building a brand as well as enhance customer acquisition (Vries, Gensler, & Leeflang, 2017). Choosing the right message format, however, is something by which many companies struggle nowadays. The best way in which companies can examine the extent towards which a certain message format is effective is by examining their impact on behavioral outcomes (Vries, Gensler, & Leeflang, 2017). Three ways in which the behavioral outcomes of the different messages can be examined are by using metrics such as brand awareness, consideration, as well as preference (Draganska, Hartmann, & Stanglein, 2014; Srinivasan, Vanhuele, & Pauwels 2010).

Similarly, Rettie (2002) argues that there are three stages which a prospect goes through in the whole customer acquisition process namely, opening the email, paying attention to the email and the response itself. This research will focus on testing what makes the prospects pay attention to a certain email as well as what makes a prospect respond positively towards a certain message format in opposed to another. The whole model of Rettie (2002) can be summarized in figure 3 in the appendix.:

Message formats are defined as a set of ideal characteristics of a message which led to different behavioral outcomes such as brand awareness, consideration, as well as preference (Rettie, 2002; Draganska, Hartmann, & Stanglein, 2014; Srinivasan, Vanhuele, & Pauwels 2010)

There are two hypotheses that are associated with this theoretical framework which Rettie (2002) discusses, namely that the response rate is inversely related to the length of the email as well as the fact that higher response rate correlate with more appealing incentives. The literature gap that Vries, Gensler, & Leeflang (2017) recommend to be studied in the future is to enhance the knowledge about the relative effectiveness of the different message format and examine their relations in specific settings. We can consider that having a shorter email can be classified as different message format (Aspara, 2011).

Consequently, Aspara (2011) demonstrates that under conditions of change, trends and turbulence, the traditional CRM becomes less effective (Benner & Tushman, 2003). Therefore, it is essential that the salespeople/marketing people solve a particular environmental turbulence which is timely with the latest trends and developments which in return increases the customer acquisition likelihood.

H2: A message format which is short and has appealing incentive from the perspective of the customer increases the customer acquisition likelihood.

2.4 Various Firmographics that are associated with Customer acquisition probability

There are various strategies which help companies to develop profitable customer relationships. Metrics such as customer lifetime value measure the customer acquisition and retention in general (Kumar, 2010). The wheel of fortune of Kumar (2008) combines various aspects strategies that companies can do in order to maximize the lifetime value. This section, however, will focus on analyzing the effect of pitching the right product to the right customer, at the right time on increasing the customer lifetime value of the companies. The overall summary of all aspects of Kumar (2008) can be summarized as follows (the red circle indicates the relationship that is being studied in this research as found in the appendix in figure 4).

In today’s fast-paced corporate environment, salespeople and marketeers are constantly busy with predicting the next product which the customers are likely to buy. The ideal strategy can be defined as one where the firm can deliver a message which is relevant to the product and is more likely to be purchased by the targeted customers (Kumar, 2008).

This can only be achieved by having accurate predictions of the purchase sequences by looking at patterns of customers in the past that have purchased similar or same services (Kumar, 2008).

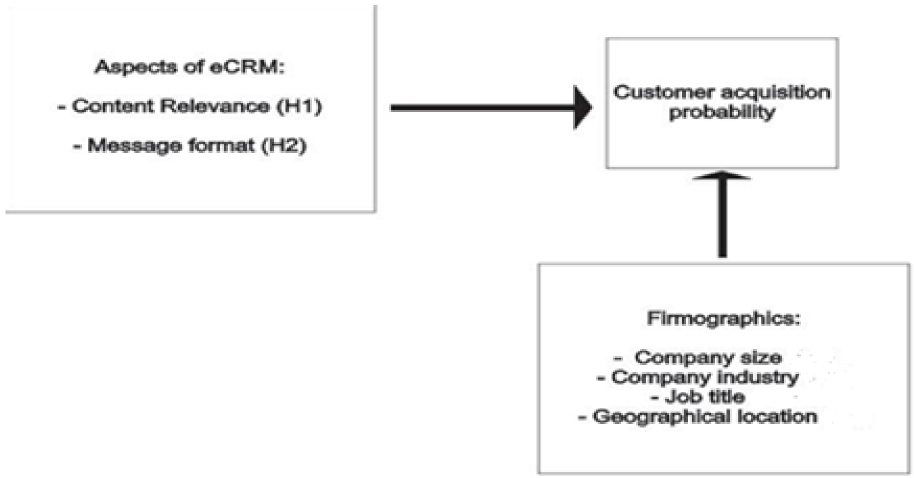
The need for having accurate predictors of the ideal customer profile emerges from the fact that in that way firms can increase the percentage of customer that are being acquired. In fact, Kumar, Venkatesan & Reinartz (2006) noticed that in a B2B setting, 85% of the customer that are predicted by their model to make a purchase, actually went to do so, whereas when companies they use the traditional model, they obtained only 55% conversion rate. Therefore, when firms get a better understanding of the ideal customer profile, they increase the acquisition likelihood. Understanding the ideal customer profile includes a deeper understanding of various firmographics (Kumar, 2008).

The current literature suggests that targeting the correct company size, company industry, job title, location, and looking at the year in which a certain company was found can all be predictors/ patterns of an improved customer acquisition process. Firstly, Pozza, Goetz, & Sahut (2018) propose in their model that company size and company industry are two of the three control variables in their framework that increase customer acquisition. Similarly, Bacon (1992) proofed with his survey that the purchasing rate of the different job titles within different companies varied within the information technology industry. Finally Rettie (2002) claims that the geographical location of countries can affect the customer acquisition likelihood as the prospects that are located in countries that receive less emails have a higher customer acquisition likelihood.

Following the theory mentioned earlier, the following conceptual framework will be examined in this deductive study:

Figure 5

Conceptual framework



Note. Aspects of eCRM and Firmographics that are predicted to affect positively the dependent variable: "customer acquisition probability"

Figure 6 provides an overview of the key papers that are being used in this paper as well as a checklist of concepts mentioned per paper.

The key terms used to find these articles are: "eCRM" and "customer acquisition probability" ; "content relevance" and "customer acquisition probability" ; "message format and "customer acquisition probability; "company size" and "customer acquisition probability"; "company industry" and "customer acquisition probability"; "job title" and "customer acquisition probability" ; "geographical location" and "customer acquisition probability.

Figure 6: Review of main articles used and key terms that are relevant

Author/s	eCRM	CRM	Content relevance	Message format	Customer acquisition	Job title	Location	Industry	Size
(Pozza, Goetz, & Sahut, 2018)	No	Yes	No	No	Yes	No	No	Yes	Yes
(Becker, Greve, & Albers 2009)	No	Yes	No	No	Yes	No	No	No	No
(Shoniregun et al., 2004)	Yes	Yes	No	No	Yes	No	No	No	No
(Singh & Saini, 2016)	No	Yes	No	No	Yes	No	No	No	No
(Aspara, 2011)	No	Yes	No	Yes	Yes	No	No	No	No
(Benner & Tushman, 2003)	No	Yes	No	Yes	Yes	No	No	No	No
(Hussain & Saberi, 2012)	No	Yes	Yes	No	Yes	No	No	No	No
(Bacon, 1992)	No	Yes	No	No	Yes	Yes	No	No	No

(Winer, 2001)	No	Yes	No	No	Yes	No	Yes	No	No
Heinonen & Strandvik (2007)	No	Yes	Yes	No	No	No	No	No	No
Kumar, Jacquelyn, & Reinartz (2005)	No	Yes	Yes	No	No	No	No	No	No
Moriatry & Spekman, (1984)	No	Yes	Yes	No	No	No	No	No	No
Kumar & Venkatesan, (2004)	No	Yes	Yes	No	No	No	No	No	No
(Jarvien & Taiminen, 2016)	No	Yes	Yes	No	No	No	No	No	No
Sahni, Wheeler & Chintag	No	Yes	Yes	No	No	No	No	No	No

unta (2018)									
(Kumar & Reinartz, 2016)	No	Yes	No	Yes	No	No	No	No	No
Epp & Price, 2008; Gupta, Hagerty & Myers, 1983)	No	Yes	No	Yes	No	No	No	No	No
Vries, Gensler, & Leeflang (2017)	**No**	Yes	No	Yes	No	No	No	No	No
Srinivasan, Vanhuele, & Pauwels 2010)	No	Yes	No	Yes	No	No	No	No	No
Rettie (2002)	No	Yes	No	Yes	No	No	Yes	No	No

Kumar (2008)	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Kumar, Venkatesan & Reinartz (2006)	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes
(Draganska, Hartmann, & Stanglein, 2014	No	Yes	No	Yes	No	No	No	No	No

The next section shall provide additional information about the research design of this paper.

3 Methodology

In order to explain the research design of this paper, this paper will explain the analysis method that will be applied with measures per variable, the ways in which reliability and validity is ensured, and additionally will explain the main goal of this research, the research approach that will be applied, the research strategy that will be used, the time horizon of the overall research, and the data collection method that will be used as well as the operationalization and measurement instruments associated with each of the variables.

Firstly, goal of this research as seen from chapter 1 is to find out what are the eCRM and firmographic predictor variable that increase the customer acquisition likelihood of prospects. Since this research will rely on statistics only, we can conclude that the research philosophy that will be applied is positivistic.

Secondly, because we have already developed hypotheses and are testing a pre-existing theory and then formulated the research approach respectively, we will be dealing with a deductive research approach (Silverman, 2013; Babbie, 2016).

Thirdly, in terms of a research strategy, this paper will use a unique dataset of observation towards which the research question was tested in order to examine each of the hypotheses. The company where the overall data was gathered is called the entity in this paper. The entity is a cloud-based eLearning authoring software which is used by enterprises such as Unilever, Walmart and T-mobile to scale knowledge sharing amongst the workforces. The entity enables trainers and subject matter experts to rapidly create the most engaging courses that have the highest learning impactIn addition, the company is making efforts to increase its customer acquisition process by targeting companies from different sizes, industries and other characteristics in their outbound efforts.

Next, when talking about a time horizon, this research will be using a cross-sectional approach. This is so, as the expected duration of the whole research is around 6 months and there will be no time left for a longitudinal study (Babbie, 2016).

Finally, in terms of data collection methods, this research will be using simple random sampling by trying to select n=2500 responses of the survey out of the n=5000 in order to meet the requirements for the logistic regression model (Babbie, 2016).

3.1 Analysis method and measures

In general, in the quantitative marketing literature, there are two various analyses which are applied when it comes to having a dichotomous dependent variable. This paper will use two methods of analysis to examine the relationships that are being studied which will be namely the logistic regression and the linear discriminant analysis (Peng et al., 2002). Both techniques because of their nature depend on strict assumptions such as the normality of the independent variable, linearity of the relationships, lack of multicollinearity between the independent variables, and equal dispersion matrices for the discriminant analysis (Hair et al., 1998). Dawes et al. (1997) states that although both the discriminant analysis and the logistic regression could be interchangeably used for quite a huge part of the analysis, the logistic regression technique has two major advantages when compared to the linear discriminant analysis which are namely the fact that it is more robust to violations of assumptions of the multivariate normality and equal variance-covariance metrices across groups, and it is similar to regression with its more easily interpretable diagnostic statistic. Moreover, there are further advantages which raise the popularity of the logistic regression which come from the following assumptions: the logistic regression does not assume linear relationship between variable x and y, the independent variable that are being studied do not have to be with an interval measure, the independents are not required to be unbounded, and the normally distributed error terms are not assumed.

The relevance table in figure 7 in the appendix. will provide detailed information on the measures of each variables that are being studied.

3.2 Logistic Regression

The logistics regression, which was developed later in the 1960s and 1970s, is a well-known simple technique which is used in the traditional marketing applications which provides robust and quick results (Neslin et al., 2006; Bucklin & Gupta, 1992; Peng et al., 2002). This technique provides a closed-form solution for the “a posteriori” probabilities as it tries to maximize the log-likelihood function to become an appropriate fit for the data that is being studied (Allison, 1999). It is recommended not to include all the predictors into one regression model as it would often result in overfitting and poor predictions in certain settings where many variables may have little to add to the prediction model (Allison, 1999). Therefore, this research will separate the eCRM aspects that may have influence over the customer acquisition likelihood and the various firmographics. The variable selection therefore improves the comprehensibility of the resulting model as the resulting models will generalize better (Kim, 2006).

The first proposed analysis of method chosen for all the six hypotheses is logistic regression due to the fact that we will be predicting a dichotomous dependent variable.

The logit of the multiple regression model is summarized as follows:

$$\mu_{y/x} = \frac{e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots\ldots\beta_n x_m)}}{1+e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots\ldots\beta_n x_m)}}$$

(Akinci, Kaynak, & Aksoy, 2007)

Once the logit transformation is made, the following equation is given:

$$\mu_p = \log = \left[\frac{\mu_{y|x}}{1-\mu_{y|x}}\right],$$

And as a result, the following equation is brought into the table:

$$\mu_p = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_m.$$

(Akinci, Kaynak, & Aksoy, 2007)

Where μ is the binary dependent variable which in this case is “customer acquisition” that also will represent the outcome (μ=1 if customer replies positively, by which we mean agrees for a phone call to explore the entity further and , y=0 otherwise) (Babbie, 2016).

When it comes to the independent variables (x1.,x2,x3,x4,x5,x6 will represent “content relevance”, “message format”, “company size”, “company industry”, “job title”, “company location” and “company year found” respectively.

In addition, β0, β1, β2, β3, β4, β5, β6 are the regression coefficients that will be estimated the maximum likelihood method based on the data.

Bucklin & Gupta (1992) and Neslin et al. (2006) argue that the logistic regression technique is popular for three main reasons. Firstly, it is a closed-form solution for posterior probabilities that are available. Secondly, the proposed logistic regression technique is conceptually simple. Thirdly, the logistic regression provides robust results that are quick when compared to other classification techniques.

The next subsection will provide extra information on the linear discriminant analysis and the way in which it will be applied in this research

3.3 Linear Discriminant Analysis

The Hosmer and Lemeshow of the logistic regression demonstrated a statistically significant outcome, which illustrates that there is some misspecification in the predictive capacity of the model. Because of that, it would be wise to use one more model - the Linear Discriminant Analysis, in order to make sure and align the findings in order to test the extent towards which the Logistic Regression results are confirmed by it.

The linear discriminant analysis classifies objects by a set of independent variables into one of two or more exhaustive and mutually exclusive categories (Morrison, 1969).

Denote:

X_{ij} = ith individual value of the jth independent variable where i=… j= 1,2,3,4,5,6

B_j= Discriminant coefficient of the jth variable where j=1,2,3,4,5,6

Z_i = The ith individual's discriminant score, where i=…

Z_{crit} = the critical value for the discriminant score

(Morrison, 1969)

Furthermore, the linear classification procedure can be explained as follows:

$Z_i = B_0 + B_1X_{1i} + B_2X_{2i} \ldots\ldots + B_nX_{ni}$

The classification procedure later on is divided into two main steps:

- Classify individual i to belong to Group 1 if $Z_i > Z_{crit}$
- Classify individual i to belong to Group 2 if $Z_i < Z_{crit}$

As a result, the classification boundary will be the locus of points in which

$B_0+B_1X_{1i}+\ldots.+B_nX_{ni}= Z_{crit}$

Where n= (the number of independent variables)= 6, the classification boundary is therefore in the 3+ dimensions (6).

Each of the individuals on one side of the line is classified in Group 1, and on the other side is classified as Group 2.

Next, denote μj1 to be the mean of the jth independent variable for the individuals that belong to group 1 (j=1,2,3,4,5 or 6).

Next, denote σ1jk to be the covariance between variables j and k for individuals that belong to group 1

The mean vector μ1 = (μ11, μ21, μ31, μ41, μ51, μ61).

As a result the covariance matrix V1 =

$$\mathbf{V}_1 = \begin{bmatrix} \sigma_{11}^1 & \sigma_{12}^1 & \cdots & \sigma_{1n}^1 \\ \sigma_{12}^1 & \sigma_{22}^1 & \cdots & \sigma_{2n}^1 \\ \vdots & \vdots & & \vdots \\ \sigma_{1n}^1 & \sigma_{2n}^1 & \cdots & \sigma_{nn}^1 \end{bmatrix}.$$

(Morrison, 1969)

σ111 is merely the variance of X1. Furthermore, the covariance between Xj and X1 = The covariance between X1 and Xk. Therefore, we can conclude that such matrix is symmetrical. In addition, the covariance which was described earlier is related to the correlation between two variables.

Denote rjk as the correlation between Xj and Xk. As a result we obtain:

$$r_{jk} = \frac{\sigma_{jk}}{\sqrt{\sigma_{jj}\sigma_{kk}}}.$$

(Morrison, 1969)

Similar definitions hold for the mean vector µ2 and covariance matrix V2. Given these preliminaries, the conditions for optimality of a linear classification can be stated. The linear classification procedure can be classified as optimal if a) the independent variables in both groups are multivariate normal with mean vectors µ1 and µ2 and covariance metrices V1 and V2 respectively, and b) if V1=V2

In summary, there are several considerations/ requirements that need to be met when applying the linear discriminant analysis. Firstly, a linear discriminant analysis is appropriate if the group covariance matrices are equal (or nearly equal) as demonstrated earlier. Next, the D2 statistics, which can be transformed to F-statistics if needed, tests the statistical significance of the difference between the groups that are being studied. Thirdly, the researcher needs to be aware of the potential upward bias that can exist as we are using a classification of the same individuals in order to calculate the discriminant function. Furthermore, the researcher needs to consider the different chances that the models can result when groups have a different sample size. Moreover, the effective sample size in general is governed by smaller groups. Next, the researcher needs to check if the discriminant coefficients are normalized by the standard deviations of the independent variables. Moreover, the researcher that applies the discriminant analysis needs to be sure that prior probabilities as well as the opportunity costs of the misclassification were considered. Finally, the researcher needs to check if the independent variables that are used for discrimination are operational (Morrison, 1969).

3.4 Validity

Validity refers to the justification of the way in which a certain data in the research is generated (Swanborn, 1996a). There are four major type of validity which one should consider when writing a research paper: pragmatic validity, external validity, internal validity, and construct validity (Babbie, 2016). Firstly, the pragmatic validity refers to a validity being both concurrent and predictive by having other instruments measure the same thing and ensuring the same results and being able to make accurate predictions with the results (Aken et al., 2007). The first measurement instrument will be the logistic regression and the linear discriminant analysis will be used in order to verify the analysis that were given by the logistic regression. Thirdly, external validity is about generalizing the results to other situations (Aken et al., 2007). Since our research question focuses on the predictor variables that strengthen the relationship between eCRM and customer acquisition probability in an empirical sense and is quantitative research, we do aim at generalizing the results and forecasting. Finally, construct validity is about the instruments that measures and whether it measures what it is supposed to measure. There has been found support in the literature that the logistic regression is the right tool to measure by Bucklin & Gupta (1992) and Neslin et al. (2006) who list three different reasons which were mentioned earlier as well.

The aim of this research is to be unbiased as much as possible owing to the fact that we utilized two measurement methods in order to verify each of the hypotheses, namely the logistic regression as well as the linear discriminant analysis. The inter validity was accomplished as the researcher performed his duty and data collection at the Rotterdam the entity's office and used as data gathering tools a set provided by the company. The sample size isn't small at all N= 124 408. Babbie (2016) argues that sample size is one of the main components that influences validity of researches. All assumptions were tested and verified in order to ensure this index.

3.5 Reliability

The second criterion for judging the credibility of a research is reliability (Babbie, 2016). The official definition of reliability states that a research is reliable when the results are independent and a researcher would achieve the same results if he/she is to conduct the result again (Swanborn, 1996a). Okamura, Etani & Doho (2010) demonstrated in his research that the logistic regression is a reliable method to be used when having a dichotomous dependent variable and metric independent variables. The model will be tested again with the linear discriminant analysis as mentioned in section In order to ensure reliability, a comparison between different sources will be made (internal consistency) (Babbie, 2016). The idea of this index is that the results need to be independent from the author of this thesis by having a data which is replicable and the same results need to be discovered if re-analyzed. The data set is provided to the two readers of this thesis for this purpose.

4 Results

In this section, we will display the general results of N= 124 408 data set by testing the effect of each of the six independent variables that were listed previously (the six hypotheses) on customer acquisition probability. We are testing 2 eCRM indicators are independent variables which are content relevance and message format. Further to that, we are testing the effect of 4 firmographics on customer acquisition probability which are namely company size, company industry, job title, and company location respectively. We will do so by the logistic regression. Next, we will display the results of the linear discriminant analysis. Afterwards, a comparison between the two measurement methods will be made. Moreover, we will ensure the validity, reliability and the controllability of the overall research before moving to the discussion and the recommendation chapter.

4.1 Logistic regression General Results

Before applying the binary logistic regression, there are several assumptions that need to be verified. Firstly, the dependent variable should be binary. In this case the customer acquisition likelihood's outcome are 0 if the prospect responded negatively and 1 if they responded positively, hence this assumption is met. Secondly, the logistic regression requires the observations to be independent from one of each other. Phrased differently, the observations should not come from matched data or repeated measurements. Luckily, all the duplicate values were removed from the dataset before being uploaded to SPSS, which means that this assumption is met as well. Thirdly, it is required that in the logistic regression, there is little to no multicollinearity among the independent variables. Looking at Figure 8 in the appendix, we can see that indeed little/no multicollinearity between the independent variables and the dependent one.

Next, the logistic regression assumes linearity of the log odds as well as the independent variables. Although, the logistic regression does not require the independent and dependent variables to be related linearly, it does require that the independent variables are linearly related with the log odds. As a rule of thumb, there are required 10 cases with the least frequent outcome of each of the independent variables in the model. In order to verify this assumption, we will have a look at some descriptive statistics in the three figures in the appendix Figures 7, 8 and 9 respectively.We can observe from figure 10 in the appendix that the total sample size of this research would be 124 408. Looking at the frequency of the independent variables company size, location, CP Position, industry, and message format, we can see that for each of categories 0-6 (for some the upper number can be less than 6) are greater than 10. Following these arguments, the fourth assumption of the logistic regression is met as well.

The variables in the equation table as observed in figure 11 in the appendix, tests whether the positive and the negative responses are statistically significantly different from each other. The null hypothesis here would be that there is an equal number of people within the sampling variability in the positive vs negative responses. The alternative hypothesis on the other hand, would be that there is an unequal number of people within the sampling variability in the positive vs negative responses.

Given the $p<5\%$, we have enough evidence to reject the null hypothesis, which means that the probability that the outcome of the e-mail campaign between a positive/negative response is not the same.

Next, looking at the Exp(B) as observed in figure 11, we find that there is 98,6% chance greater likelihood that the prospects respond negatively, meaning that the customer acquisition likelihood probability here would be 1,4%.

We discover that in the “variables not in the equation” table (Figure 12 in the appendix), that there are 20 potential predictor variables - content relevant, message format, CP position variables (4 of them), location variables (6 of them), industry variable, and 7 company size variables.

Analyzing each variable separately, we can make several conclusions. Firstly, the content relevance is statistically significant with a positive score of 6,7017. Same can be concluded for all the variables except, Company size (5), and company size (6) which are statistically insignificant. Next, we can conclude that firms that have prior knowledge on what the ideal company size range fits into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect except for the categories of 5000-10 000 headcount as well as 10 000+ headcount for which we have no enough evidence to make a case

Next, the omnibus test of model coefficient (as observed in figure 13 in the appendix), is testing the hypothesis on whether or not there is at least some predictive capacity in the regression equation (Babbie, 2016). Given the Chi-Square value illustrated in this table, we can conclude that it is indeed statistically significant. Therefore, we feel confident that there's something happening in the model summary table and the results observed there have to be taken seriously.

Furthermore, the model summary table (figure 14 in the appendix) illustrates that approximately 4,9% of the variability in the dependent variable (Result) is accounted for by independent variables.

Next, given the statistically significant outcome of the Hosmer and Lemeshow test (figure 15 in the appendix), we can conclude that there is some misspecification in the predictive capacity of the model. Because of that, it would be wise to use one more model which will be applied later - the Linear Discriminant Analysis, in order to make sure and align the findings in order to test the extent towards which the Logistic Regression results are confirmed by it.

Consequently, the contingency table for hosmer and lemeshow test (figure 16 in the appendix), segments the predicted probabilities into 10 different categories and also accounts the number of people in those categories as well as conducts comparisons them against the expected versus the observed result and the difference between the expected and the observed result, which in return becomes greater the less predictive capacity the model possesses, and the larger the chi-square value is, the less reliable the model is (Babbie, 2016).

Figure 37

Variables in the equation

	B	S.E.	Sig.
ContentRelevance	-,373	,059	,000***
MessageFormat(1)	-,044	,091	,628
CP Position			,000
CP Position(1)	,300	,214	,160
CP Position (2)	,229	,218	,293
CP Position(3)	-,275	,225	,220
Location			,000
Location(1)	-,953	,273	,000***
Location(2)	,160	,289	,578
Location(3)	,190	,273	,485
Location(4)	1,361	,283	,000***
Location(5)	-,798	,314	,011
Industry(1)	-,291	,075	,000
CompanySize			,001
CompanySize(1)	-1,500	1,004	,135
CompanySize(2)	,302	,139	,029**
CompanySize(3)	,228	,080	,004***
CompanySize(4)	,274	,084	,001***
CompanySize(5)	,163	,063	,010**
CompanySize(6)	,204	,092	,027**
	-3,947	,359	,000

**Star represent sig level
*** - p<.001, **p<.01,
*p<.05**

In this category, we would be looking at the scores of the predicting variable, by keeping in that an increasing score in any of them would result in increased likelihood of customer acquisition probability. Similarly, a negative score in any of the predicting variable would results in decreased likelihood of customer acquisition (Babbie, 2014).

Firstly, we need to identify the statistically significant variables with alfa level at 5%. These are content relevance, location (1) and (4), and company size (2,3,4,5,6). These codes refer to content relevance at both same and similar companies, geographical locations including Canada and New Zealand & Australia, other industries (except apparel & fashion, business supplies and telecom).

The statistically insignificant variables are message format (1), CP Position (1), CP Position (2), CP Position (3), Location (2), Location (3), Location (5), and company size (1), which refer to traditional message format, CP Position Specialists L&D, training, talent management, people development, : heads, directors and managers of HR (new field that the company hasn't explored yet), and specialists HR (new field that the company hasn't explored yet). From the locations the insignificant subcategories are the European countries, Middle East & New Zealand, and others.

We can only make definite conclusions for this model based on the statistically significant variables.

4.2 Linear Discriminant analysis General Results

The linear discriminant analysis very much like the logistic regression, allows us to determine the probability of group membership by being based on several predictor variables. In this methodology, the independent variables are predictors and dependent variables are the groups. This means that the following variables are the predictors: "aspects of eCRM" and "firmographics", and the group will be "customer acquisition probability" which is also defined as the outcome variable.

Assumptions:

Just like the logistic regression, in the linear discriminant analysis, it is crucial to verify the assumptions required for conducting the test to proceed to the next stage.

The assumptions that need to be proven for this model are multivariate normality, homogeneity of variance, multicollinearity, and independence. All these overlap with the assumptions that we have proofed already in the logistic regression model, therefore, we can proceed to the descriptive statistics.

The first table (figure 19 in the appendix)– namely the analysis case processing summary shows us that we have a population of total N= 124 408 observations, all of which are valid.

Next, figure 20 in the appendix illustrates descriptive statistics regarding the number of predictive variables for each of the aspects of eCRM and firmographics within the groups 0 and 1 which refer to a negative response for a call and a positive response for a call as per figure 4. Moreover, we can see that the standard deviation are the highest at negative as well as positive response rates for location as well as company size with 1.18, 1.54, 1.16, and 1.56 respectively.

Looking at the test of equality of group means (figure 21 in the appendix), there are several conclusions that can be made regarding each of the predictor variables. Firstly, the content relevance component is statistically insignificant. Next, all the other variables, namely message format, CP position, location, industry, and company size are statistically significant.

In an ideal world, the predictors at the pooled within groups matrices shouldn't be highly correlated with one another as this is one of the assumptions for the linear discriminant analysis. There are several relationships which we need to keep an eye from. There seems to be a negative correlation between CP position and content relevance, location and message format. The other relationships seem to be independent from each other, as observed in figure 22 in the appendix.

Next, the ranks and natural logarithms of determinants printed are those of the group covariance matrices.

Looking at the log determinants table, we can conclude that all 3 values displayed are fairly similar as they vary between -14,098 up to -14,517 as observed in figure 24 in the appendix.

Figure 25, tests null hypothesis of equal population covariance matrices. The significance for Box's M is less than the alfa level of 5%. Therefore, we have enough evidence to reject the null hypothesis of equal variation population covariance matrices.

Furthermore, the standardized canonical discriminant function coefficients table (figure 28 in the appendix) illustrates the relative importance of the six predictors and we can see that "location" has the highest importance with a coefficient of -0,93. The next two strongest predictors are industry and CP position with indices of -0,38 and 0,38 respectively. The content relevance is fourth with an index of 0,31 and company size is fifth with an index of 0,17. The message format seems to be the worst predictor within the whole equation with an index of -0,003.

When looking at the structure matrix (figure 29), it is important that we find consistency between the standardized canonical discriminant function coefficients table and the structure matrix. When we classify the predictors, location is again the highest predictor. Message format, however, is the second highest index here which indicates that we can't make definite conclusions regarding the extent towards which it has an impact on the overall model based on the linear discriminant analysis model.

Next, figure 35 in the appendix, provides us with both specificity as well as sensitivity of the variables. In the best-case scenario, the predicted group membership in this table is accurate. Within the original predicted group membership, 71,7% were found to give negative response rates, therefore this is the percentage of specificity as well. The positive response sensitivity is classifying as 55,1%, so the specificity of the positive response rates is 55,1%. A high sensitivity result would mean that there are a few false negatives, whereas a high specificity score would indicate that there are a few false positives. So, this model has relatively high sensitivity and specificity indices.

In the cross validated section, the percentages are the same and we can see that 71,5% of the original grouped cases and cross-validated grouped cases are correctly classified.

5 Discussion

Discussion on logistic regression:

As discussed in the initial sections, this research examines the following hypotheses:

H1: A message with high content relevance from the perspective of the customer increases the customer acquisition probability.

Content relevance is statistically significant which indicates that this hypothesis holds true.

H2: A message format which is short and has appealing incentive from the perspective of the customer increases the customer acquisition likelihood. Message format has an insignificant coefficient at p-level of alfa = 5% , therefore we can conclude that a trend message nor a traditional sales message doesn’t contribute to the output of customer acquisition probability.

We can make several conclusions for the firmographics that we studied as well. For example, it was examined if firms that have prior knowledge on what the ideal company size range fits into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect. .This holds true for the groups (2,3,4,5,6) which refer to the 201-500, 501-1000, 1001-5000,5001-10 000 headcount, but doesn’t hold true for the 51-200 group of company headcounts prospected, as the first 5 groups listed have a beta coefficient of 0.302, 0.228, 0.274, 0.163, 0.204 all positive, but not for the 51-200 as its p-value is insignificant.

Moreover, it was examined if firms that have prior knowledge on what the ideal company industries fit into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect.

We have a statistically significant result for the industry (1), but not (0) which means that all other industries outside the ones that the company thought would be good for them have a negative .291 coefficient with customer acquisition probability. In other words, prior knowledge of the ideal customer profile of the so-called other industries doesn't increase the likelihood of firms acquiring a prospect.

Next, it was examined if firms that have prior knowledge on what the ideal job title fits into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect. Here, we cannot make any conclusions as all CP Position (1,2, and 3) are statistically insignificant.

In addition, it was examined if firms that have prior knowledge on what the ideal geographical location fits into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect. This is the part where it gets interesting. Prior knowledge of geographical locations 1 and 4 increases the acquisition probability, but prior knowledge of 2,3, and 5 doesn't. This means that the better prospects for the company in question are based in Canada and Australia.

Discussion on linear discriminant analysis:

The hypotheses and the outcome are listed as follows:

H1: A message with high content relevance from the perspective of the customer increases the customer acquisition probability.

The content relevance index demonstrates a score of 0,31 within the standardized canonical discriminant function coefficients table and a score of -0,07 which is the lowest out of all scores within the structure matrix. Therefore, it would be reasonable to verify the extent towards which content relevance influences the customer acquisition probability within the logistic regression model as no definite conclusion can be made via the linear discriminant analysis.

H2: A message format which is short and has appealing incentive from the perspective of the customer increases the customer acquisition likelihood.

According to the standardized canonical discriminant function coefficient, the message format was the worse predictor with an index of -0,003, however, in the structure matrix, it was the second highest predictor. A good idea therefore would be to align these findings with the logistic regression that is being conducted in this research as no definite findings can be made for that component within the linear discriminant analysis model.

In this model, we can make several conclusions regarding the firmographics as well. Firstly we examined if, firms that have prior knowledge on what the ideal company size range fits into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect. .

Both the standardized canonical discriminant function coefficients as well as the structure matrix demonstrate that firms that have prior knowledge on what the ideal company size range fits into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect with respective indices of 0,017 and -0,129.

Secondly, we examined if, firms that have prior knowledge on what the ideal company industries fit into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect.

Company industry was the second strongest predictor within the standardized canonical discriminant function coefficients table with an index of -0,38. The findings of the structure matrix align with an index of 0,151. Therefore, firms that have prior knowledge on what the ideal company industries fit into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect.

Thirdly, we examined if firms that have prior knowledge on what the ideal job title fits into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect.

A similar pattern is observed within the job title index. Job title was the second strongest predictor within the standardized canonical discriminant function coefficients table shared with the company industry variable with an index of 0,38. The findings of the structure matrix align with an index of -0,087. Therefore we can conclude that firms that have prior knowledge on what the ideal job title fits into the “ideal customer profile criteria”increases the likelihood of firms acquiring the prospect.

Next, we examined if firms that have prior knowledge on what the ideal geographical location fits into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect**.** Targeting companies by a geographical location has an effect on the relationship between eCRM and customer acquisition.

From this research, it seems that firms that have a prior knowledge on what the ideal geographical location fits into the ideal customer profile criteria have the greatest likelihood of acquiring customers with indices of -0,93 and 0,516 respectively.

6 Recommendations and conclusions

In this section, we will summarize each of the conclusions based on the logistic regression model and the linear discriminant analysis model and will make final conclusions and recommendations to future business development representatives and salespeople dealing with outbound processes.

The hypotheses are read as follows:

H1: A message with high content relevance from the perspective of the customer increases the customer acquisition probability.

Logistic regression: Content relevance is statistically significant which indicates that this hypothesis holds true.

Linear discriminant analysis: The content relevance index demonstrates a score of 0,31 within the standardized canonical discriminant function coefficients table and a score of -0,07 which is the lowest out of all scores within the structure matrix. Therefore, it would be reasonable to verify the extent towards which content relevance influences the customer acquisition probability within the logistic regression model as no definite conclusion can be made via the linear discriminant analysis.

Conclusions & recommendations: Owing to the fact that the LDA requires us to verify the results with the log regression, we can conclude that the hypothesis holds true. Interestingly, Bleier & Eisenbeiss (2015) have a similar experience as to where they mention that a degree of content personalization are effective when a consumer has an initial impression of the product/service that they purchase, but quickly lose effectiveness as time passes since that last visit – this phenomena is called as over personalization. With the entity, this experience is similar as personalization when it comes to job title increases acquition likelihood with the right message format when personalized by job title, but loses effectiveness when personalized by problem-related industry points are brought.

H2: A message format which is short and has appealing incentive from the perspective of the customer increases the customer acquisition likelihood.

Logistic regression: Message format has an insignificant coefficient at p-level of alfa = 5% , therefore we can conclude that a trend message nor a traditional sales message doesn't contribute to the output of customer acquisition probability.

Linear discriminant analysis: According to the standardized canonical discriminant function coefficient, the message format was the worse predictor with an index of -0,003, however, in the structure matrix, it was the second highest predictor. A good idea therefore would be to align these findings with the logistic regression that is being conducted in this research as no definite findings can be made for that component within the linear discriminant analysis model.

Conclusions & recommendations: The two models align that this variable has little/nothing to do with increasing customer acquisition probability. Interesting future research recommendation would be to verify the extent and whether or not personalization in terms of a message format (trend oriented-traditional) at high level of content relevance has diminishing returns in the long run when it comes to output.

It was also examined if firms that have prior knowledge on what the ideal company size range fits into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect.

Logistic regression: This holds true for the groups (2,3,4,5,6) which refer to the 201-500, 501-1000, 1001-5000,5001-10 000 headcount, but doesn't hold true for the 51-200 group of company headcounts prospected, as the first 5 groups listed have a beta coefficient of 0.302, 0.228, 0.274, 0.163, 0.204 all positive, but not for the 51-200 as its p-value is insignificant.

Linear discriminant analysis: Both the standardized canonical discriminant function coefficients as well as the structure matrix demonstrate that firms that have prior knowledge on what the ideal company size range fits into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect with respective indices of 0,017 and -0,129.

Conclusions & recommendations:

For the company in question, we recommend that they would target all the headcount companies above 200 as knowledge of this variable increases the likelihood of customer acquisition probability. Generally for all other companies, they should make sure that this variable is known to them before they start their prospecting processes so that they have higher customer acquisition probability as well.

In addition, It was also examined if firms that have prior knowledge on what the ideal company industries fit into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect.

Logistic regression: We have a statistically significant result for the industry (1), but not (0) which means that all other industries outside the ones that the company thought would be good for them have a negative .291 coefficient with customer acquisition probability. In other words, prior knowledge of the ideal customer profile of the so-called other industries doesn’t increase the likelihood of firms acquiring a prospect.

Linear discriminant analysis: Company industry was the second strongest predictor within the standardized canonical discriminant function coefficients table with an index of -0,38. The findings of the structure matrix align with an index of 0,151. Therefore, firms that have prior knowledge on what the ideal company industries fit into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect.

Conclusions & recommendations:

Overall, it seems that knowledge of the company industry may increase the customer acquisition probability. However, this research is limited to having 2 main categories which were mainly 0- apparel & fashion; Business supplies ;food ; retail ; electrical ; telecommunication and 1- others. It is a good idea as a recommendation for future research to split the categories into more indices in order to better understand which industries contribute to success of customer acquisition in other organizations.

Next, we examined if firms that have prior knowledge on what the ideal job title fits into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect.

Logistic regression: Here, we cannot make any conclusions as all CP Position (1,2, and 3) are statistically insignificant.

Linear discriminant analysis: Job title was the second strongest predictor within the standardized canonical discriminant function coefficients table shared with the company industry variable with an index of 0,38. The findings of the structure matrix align with an index of -0,087. Therefore we can conclude that firms that have prior knowledge on what the ideal job title fits into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect.

Conclusions & recommendations:

The logistic regression is limited from the perspective that we got insignificant scores for all subgroups. However, the linear discriminant analysis is confident that firms that have prior knowledge on what the ideal job title fits into the “ideal customer profile criteria” increases the likelihood of firms acquiring the prospect. Therefore a recommendation to all companies would be to research well the job titles that are most likely to be decision makers within organizations in order to boost their customer acquisition probability index.

Finally, we examined if firms that have prior knowledge on what the ideal geographical location fits into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect: This is the part where it gets interesting. Prior knowledge of geographical locations 1 and 4 increases the acquisition probability, but prior knowledge of 2,3, and 5 doesn't. This means that the better prospects for the company in question are based in Canada and Australia.

Linear discriminant analysis: From this research, it seems that firms that have a prior knowledge on what the ideal geographical location fits into the ideal customer profile criteria have the greatest likelihood of acquiring customers with indices of -0,93 and 0,516 respectively.

Conclusions & recommendations:

We are confident that firms that have prior knowledge on what the ideal geographical location fits into the "ideal customer profile criteria" increases the likelihood of firms acquiring the prospect as verified by the two models overall for most companies. However, the company for which this research was done, should target even more Canada (with codes 1) and Australia (and 4) as they happen to be better market fits for the value proposition that they have which was proofed by figure 37 in the logistic regression result section. This was confirmed from the canonical discriminant function coefficients table in figure 28 as "geographical location" had the highest importance as a predictor with a coe fficient score of -0,93.

7 Research limitations

The biggest limitation of this study is that the data set provided by the entity consisted of only one marketing channel which in this case is the email channel. It could very well be the case that a different experiment conducted by cold calling to the same prospects could lead to different outcome for example. Therefore, a recommendation for further research would be to consider different acquisition tools and measure the extent towards which the results vary with the current one. Next, the research was limited to the ideal customer profile being only learning and development and HR professionals and may not necessarily be valid for all other personas. Furthermore, another limitation of the research is that it only considers the corporate environment and the prospects that work in companies with a headcount of 51+ people. Moreover, the research is selective for some countries and doesn't include regions such as South America, Africa, Asia and many other countries. In addition, it may be required at some point to measure different message formats such as subject lines, sender of the email, URL link format and others in order to verify H2 tested in this research.

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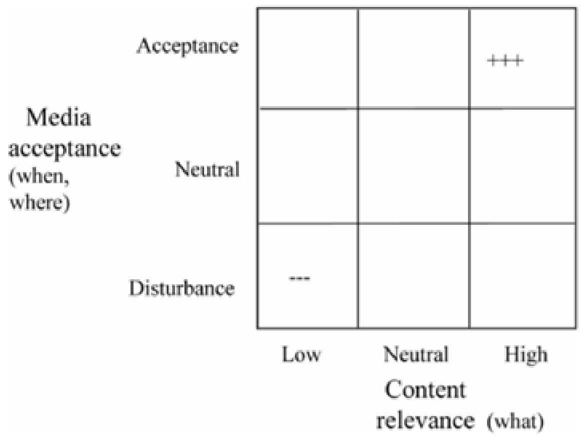
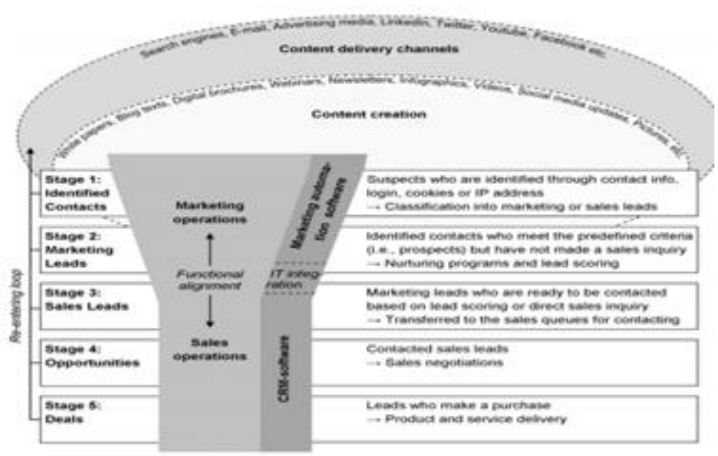
9 Appendix

Figure 1
Factors that influence consumer's responsiveness



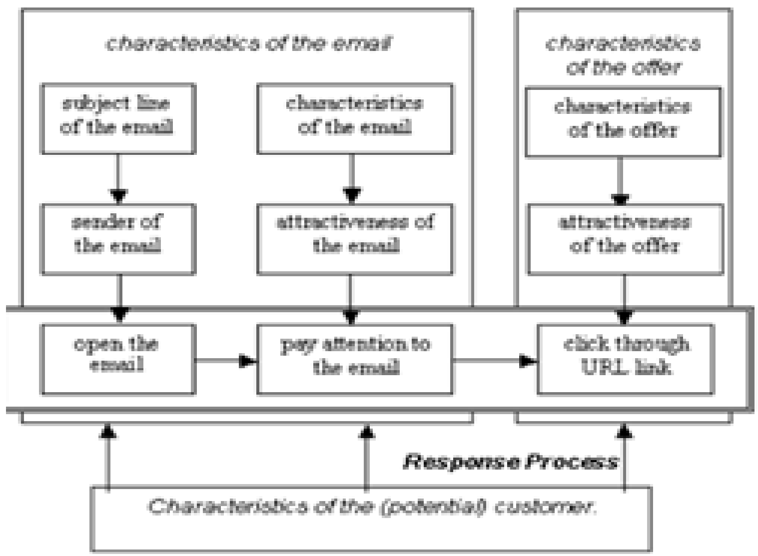
(Heinonen & Strandvik ,2007)

Figure 2
Marketing & Sales funnel



(Jarvien & Taiminen, 2016).

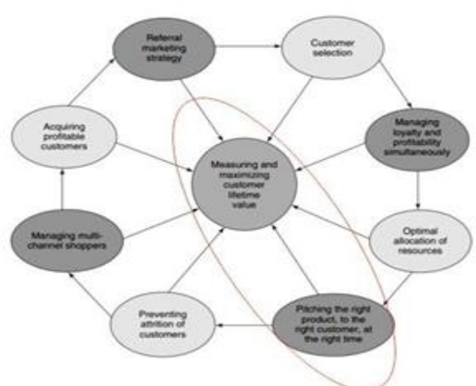
Figure 3



(Rettie, 2002)

Figure 4

The wheel of fortune



(Kumar, 2008)

Figure 6: Review of main articles used and key terms that are relevant

Author/s	eCRM	CRM	Content relevance	Message format	Customer acquisition	Job title	Location	Industry	Size
(Pozza, Goetz, & Sahut, 2018)	No	Yes	No	No	Yes	No	No	Yes	Yes
(Becker, Greve, & Albers 2009)	No	Yes	No	No	Yes	No	No	No	No
(Shoniregun et al., 2004)	Yes	Yes	No	No	Yes	No	No	No	No
(Singh & Saini, 2016)	No	Yes	No	No	Yes	No	No	No	No
(Aspara, 2011)	No	Yes	No	Yes	Yes	No	No	No	No
(Benner & Tushman, 2003)	No	Yes	No	Yes	Yes	No	No	No	No
(Hussain & Saberi, 2012)	No	Yes	Yes	No	Yes	No	No	No	No

(Bacon, 1992)	No	Yes	No	No	Yes	Yes	No	No	No
(Winer, 2001)	No	Yes	No	No	Yes	No	Yes	No	No
Heinonen & Strandvik (2007)	No	Yes	Yes	No	No	No	No	No	No
Kumar, Jacquelyn, & Reinartz (2005)	No	Yes	Yes	No	No	No	No	No	No
Moriatry & Spekman, (1984)	No	Yes	Yes	No	No	No	No	No	No
Kumar & Venkatesan, (2004)	No	Yes	Yes	No	No	No	No	No	No
(Jarvien & Taiminen, 2016)	No	Yes	Yes	No	No	No	No	No	No

Sahni, Wheeler & Chintagunta (2018)	No	Yes	Yes	No	No	No	No	No	No
(Kumar & Reinartz, 2016)	No	Yes	No	Yes	No	No	No	No	No
Epp & Price, 2008; Gupta, Hagerty & Myers, 1983)	No	Yes	No	Yes	No	No	No	No	No
Vries, Gensler, & Leeflang (2017)	**No**	Yes	No	Yes	No	No	No	No	No
Srinivasan, Vanhuele, & Pauwels 2010)	No	Yes	No	Yes	No	No	No	No	No

Rettie (2002)	No	Yes	No	Yes	No	No	Yes	No	No
Kumar (2008)	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Kumar, Venkatesan & Reinartz (2006)	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes
(Draganska, Hartmann, & Stanglein, 2014	No	Yes	No	Yes	No	No	No	No	No

Figure 7: Operationalization and measurement of variables used in the conceptual framework

Variables	Variable Description	Variable Coding and Description
Y: Customer acquisition likelihood	Set of systems and methodologies for managing customer inquiries and prospects which are generated by a variety of marketing techniques Pozza, Goetz, & Sahut, (2018).	0 – Negative response for a call (customer didn't agree for a call) 1 – Positive response for a call (customer agreed for a call that yet didn't take place)
X: Content relevance	Content relevance is one of the main factors that has influence on the consumer responsiveness within content delivery channels such as e-mails, social media, advertising media, and search engines (Heinonen &	Comparison between two Groups: 1 similar companies 2 different companies (More info on measurement on this index to be found in figure 36 in the appendix)

	Strandvik ,2007; Jarvien & Taiminen, 2016).	
X: Message format	Message formats are defined as a set of ideal characteristics of a message which lead to different behavioral outcomes such as brand awareness, consideration, as well as preference (Rettie, 2002; Draganska, Hartmann, & Stanglein, 2014; Srinivasan, Vanhuele, & Pauwels 2010)	Comparison between two Groups: - 0 trend - 1 traditional (More info on measurement on this index to be found in figure 36 in the appendix)
X: Company size	The number of employees that are working within a company Pozza, Goetz, & Sahut (2018).	Categories: - 51-200: 1 - 201-500: 2 - 501 – 1000: 3 - 1001-5000: 4 - 5001-10000: 5 - 10000+: 6
X: Company industry	A particular industry in which a particular company operates Pozza, Goetz, & Sahut (2018).	Categories - apparel & fashion; Business supplies ; food; retail ; electrical ; telecommunication – 0 -Others - 1
X: Job title	The job title that the CP has classified on LinkedIn	Due to previous knowledge for the entity (from previous customers), we know that the best titles to reach out to are: - 0: Heads & Director and Managers L&D, Training, Talent Management, People Development related - 1:Specialists L&D, Training, Talent

		Management, People Development - 2: Heads, Directors and Managers of HR (new field that the company hasn't explored yet) - 3: Specialists HR (new field that the company hasn't explored yet)
X: Company location	The geographical location in which a particular contact person is working/based	Categories: -USA - 0 (dummy coding 0 – no/ 1- yes) -Canada – 1 (dummy coding 0 – no/ 1- yes) -European Countries – 2 (dummy coding 0 – no/ 1- yes) -Middle East – 3 (dummy coding 0 – no/ 1- yes) -New Zealand & Australia – 4 (dummy coding 0 – no/ 1- yes) -others – 5 (dummy coding 0 – no/ 1- yes)

Figure 8

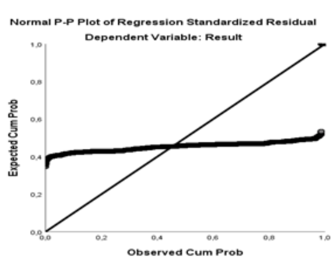


Figure 9

Case Processing Summary

Unweighted cases		N	Percent
	Included in Analysis	124408	100,0
	Missing cases	0	,0
	Total	124408	100,0
Unseleceted Cases		0	,0
Total		124408	100,0

Figure 10

Classification table

		Predicted		
		Result		
Observed		0	1	Percentage Correct
Result	0	122663	0	100,0
	1	1745	0	,0
Overall percentage				08,6

a. Constant is included in the model

b. The cut value is ,500

Figure 11

Variables in the equation

		B	S.E.	Wald	df	Sig.	Exp (B)
Step 0	Constant	-4,253	,024	31116,259	1	,000	,014

Figure 13

Omnibus Tests of Model Coefficients

		Chi-Square	df	Sig.
Step 1	Step	832,744	17	,000
	Block	832,744	17	,000
	Model	832,744	17	,000

Figure 14

Model Summary

Step	-2 log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	17523,808	,007	,049

a. Estimation terminated at iteration number 8 because parameters estimates changes less than ,001

Figure 15

Hosmer & Lemeshow Test

Step	Chi-Square	df	Sig.
1	52,842	8	,000

Figure 16

Contingency Table for Hosmer and Lemeshow Test

		Result=0		Result=1		
		Observed	Expected	Observed	Expected	Total
Step1	1	12445	12461,400	78	61,600	12523
	2	12393	12372,142	61	81,858	12454
	3	13787	13830,164	146	102,836	13933
	4	12150	12162,103	113	100,897	12263
	5	13586	13585,853	124	124,147	13710
	6	12590	12550,888	96	135,112	12686
	7	11219	11224,169	170	164,331	11389
	8	12718	12669,765	214	262,234	12932
	9	12791	12290,191	318	318,509	13109
	10	8984	9016,024	425	392,976	9409

Figure 17

Classification table

Observed		Predicted Result 0	Predicted Result 1	Percentage Correct
Result	0	122663	0	100,0
	1	1745	0	,0
Overall percentage				98,6

a The cut value is ,500

Figure 19

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		124408	100,0
Excluded	Missing or out-of-range group codes	0	,0
	At least one missing discriminating variable	0	,0
	Both missing or out of range group codes and at least one missing discriminating variable	0	,0
	Total	0	,0
Total		124408	100,0

Figure 20

Group statistics

Result					
0	Content relevance	,5359970	,49870457	122663	122663,000
	MessageFormat	,1470696	,35417674	122663	122663,000
	CP Position	,5699355	,76472788	122663	122663,000
	Location	,8335032	1,17518875	122663	122663,000
	Industry	,7876784	,40895291	122663	122663,000
	Company Size	4,6532043	1,53195211	122663	122663,000
	Predicted probability	,0138848	,01105328	122663	122663,000
	Predicted group	,0000000	,00000000	122663	122663,000
1	Content relevance	,5048711	,50011959	1745	1745,000
	MessageFormat	,0934097	,29108920	1745	1745,000
	CP Position	,5100287	,74964613	1745	1745,000
	Location	1,3776504	1,16182798	1745	1745,000
	Industry	,8429799	,36392397	1745	1745,000
	Company Size	4,4762178	1,56349978	1745	1745,000
	Predicted probability	,0239834	,02222961	1745	1745,000
	Predicted group	,0000000	,00000000	1745	1745,000
	Content relevance	,5355604	,49873586	124408	124408,000
	MessageFormat	,1463170	,35342511	124408	124408,000
	CP Position	,5690952	,76454790	124408	124408,000
	Location	,8411356	1,17673902	124408	124408,000
	Industry	,7884541	,40840612	124408	124408,000
	Company Size	4,6507218	1,53253403	124408	124408,000
	Predicted probability	,0140264	,01134897	124408	124408,000
	Predicted group	,0000000	,00000000	124408	124408,000

Figure 21

Tests of Equality of Group Means

ContentRelevance	1,000	6,702	1	124406	,010
MessageFormat	1,000	39,673	1	124406	,000
CP Position	1,000	10,564	1	124406	,001
Location	,997	368,991	1	124406	,000
Industry	1,000	31,554	1	124406	,000
CompanySize	1,000	22,951	1	124406	,000
Predicted probability	,989	1377,372	1	124406	,000
Predicted group	a				

a. Cannot be computed because this variable is constant

Figure 23

Result	Rank	Log determinant
0	7	-14,517
1	7	-14,098
Pooled within-groups	7	-14,475

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

Figure 25

Variables Failing Tolerance Test

	Within-Group variance	Tolerance	Minimum tolerance
Predicted group	,000	,000	,000

All variables passing the tolerance criteria are entered simultaneously.

a. Minimum tolerance level is 0,001.

Figure 26

Eigenvalues

Function	Eigenvalues			
1	,011[a]	100,0	100,0	,105

a. First 1 canonical discriminant functions were used in the analysis

Figure 26

Eigenvalues

Function	Eigenvalues			
1	,011[a]	100,0	100,0	,105

a. First 1 canonical discriminant functions were used in the analysis

Figure 27
Wilks' Lambda

Test of function(s)	Wilk's Lambda			
1	,989	1376,880	7	,000

Figure 27
Wilks' Lambda

Test of function(s)	Wilk's Lambda			
1	,989	1376,880	7	,000

Figure 28

Standardized Canonical Discriminant Function Coefficients

	Function
	1
ContentRelevance	,031
Message format	-,003
CP Position	,038
Location	-,093
industry	-,038
CompanySize	,017
Predicted probability	1,064

Figure 29
Structure Matrix

	Function
	1
Predicted probability	,997
Location	,516
MessageFormat	-,169
industry	,151
companySize	-,129
CP Position	-,087
ContentRelevance	-,070

Figure 30
Canonical Discriminant Function Coefficients

	Function
	1
ContentRelevance	,063
Message format	-,007
CP Position	,049
Location	-0,79
industry	-,094
CompanySize	,011
Predicted probability	94,244
(constant)	-1,295

Unstandardized coefficients

The coefficients that are observed at this table are unstandardized. Therefore, these coefficients would be part of the discriminant function equation.

Figure 31
Functions at group centroids

	Function
Result	1
0	-,013
1	,844

Unstandardized canonical discriminant functions evaluated at group means

Figure 32
Classification processing summary

Processed		124408
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		124408

Figure 32
Classification processing summary

Processed		124408
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		124408

Figure 33
Prior probabilities for groups

Result	Prior	Cases used in analysis Unweighted	Weighted
0	,500	122663	122663,000
1	,500	1745	1745,000
Total	1,000	124408	124408,000

Figure 34
Classification function coefficients

	Result 0	1
ContentRelevance	2,384	2,440
MessageFormat	2,109	2,102
CP Position	1,954	1,998
Location	-,167	-,238
industry	3,801	3,717
companySize	2,239	2,250
Predicted probability	171,484	256,027
(Constant)	-9,872	-11,425

Fisher's linear discriminant functions

Figure 35

Classification Results

		Result	0	1	Total
Original	Count	0	87995	34668	122663
		1	784	961	1745
	%	0	71,7	28,3	100,0
		1	44,9	55,1	100,0
Cross-validated	Count	0	87995	34668	122663
		1	784	961	1745
	%	0	71,7	28,3	100,0
		1	44,9	55,1	100,0

a. 71,5% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 71,5% of cross-validated grouped cases correctly classified.

Figure 36: Message types & content relevance measurements:

0- Message format: Trend message

Hi Vincent,

I saw on your LinkedIn that you have a solid background in Learning and Development at {Company name}.

One of the major 2019 Learning and Development trends is a move towards agile on-the-job learning. This accommodates today's Millennial learning expectations and enhances employee experience and retention.

Would you be available for a short call on this topic Vincent?

Kind regards,

****

T +*********

****

1- Message format: Traditional sales message

Hi Timothee,

I looked underneath your current role on LinkedIn at {Company name} and saw that your position is concerned with Learning and Development.

We have recently completed a large research with over a thousand L&D and training professionals, where it was clear that the most common challenge for them is - doing more with less. They are either facing increased training requests or decreased resources, or sometimes even both at the same time.

We have partnered up with companies like Siemens, Walmart and T-Mobile to help them to do exactly that: more with less. They are creating 5x more training for 5x less budget, using the *********platform.

Would you be available for a call this week to learn more about their approach, Timothee?

Kind regards,

****

T +*********

****

Content relevance: 1: Similar companies with too similar problems

Hi (First_name),

I see you are responsible for the learning strategy at (company_Name).

Because of that I was really curious about your thoughts - when I speak with many L&D leaders in the (Industry_name) industry they highlight the importance of embedding L&D in the business in order to not become irrelevant but have had struggles doing so.

One approach they have found effective is Employee generated learning, that way they can support learning how it naturally happens, rather than a "separate activity" outside of work.

Are you open to short 10 min talk on this topic (First_Name)?

Thanks,

****

Content relevance: 2: Different companies with similar problems

Hi Vincent,

I saw on your LinkedIn that you have a solid background in Learning and Development at {Company name}.

One of the major 2019 Learning and Development trends is a move towards agile on-the-job learning. This accommodates today's Millennial learning expectations and enhances employee experience and retention.

We at *********work with organizations such as Walmart, Siemens, and T-Mobile to leverage on this trend.

Would you be available for a short call on this topic Vincent?

Kind regards,

****

T +*********

****