

Strategies to Increase Pipeline Status: A Case Study from Eclinical Data

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ABSTRACT. In this paper we perform a case study regarding Eclinical data of Intelligent Medical Objects (IMO) which currently operates with eight pipeline statuses. It has been observed that the higher the pipeline status, the fewer consumers there tend to be. In this study, we aim to identify which factors significantly influence consumer presence at these advanced pipeline stages. Logistic regression is useful for predicting binary outcomes based on one or more independent variables. It estimates the probability of a particular outcome, allowing us to understand how different factors impact the likelihood of an event occurring. This method is widely used in fields like medicine, finance, and social sciences for classification problems and determining the significance of predictors, making it valuable for identifying key factors and making informed decisions based on probabilities. We apply logistic regression, using the probability of reaching the eighth status as our primary dependent variable. Of all the independent variables considered, only a select few are significant in explaining this outcome.

1. INTRODUCTION:

An Opportunity Pipeline is a structured framework within customer relationship management (CRM) systems, such as Microsoft Dynamics CRM, that allows businesses to visualize, manage, and track potential sales opportunities through various stages of development, from initial interest to closing a sale. Each stage in the pipeline represents a step in the sales process, helping sales teams assess where each opportunity stands, prioritize leads, forecast revenue, and identify actions needed to advance deals [8,13,16]. This tool provides a clear overview of the sales process, enabling teams to better strategize, allocate resources, and ultimately increase the chances of successful sales closures [7].

The Opportunity Pipeline in Microsoft CRM is a tool designed to help users efficiently manage, organize, and monitor business opportunities [3]. Microsoft Dynamics CRM, a customer relationship management software developed by Microsoft, primarily targets the Sales, Marketing, and Service sectors. However, Microsoft has also promoted Dynamics CRM as an adaptable XRM platform,

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encouraging partners to customize it using its proprietary framework. Intelligent Medical Objects Inc. (IMO) aims to increase customer engagement in the later stages of its pipeline, which consists of eight stages: initial engagement (S1), customer follow-up (S2), T & C pricing decision (S3), contract initiated (S4), contract negotiations (S5), alignment complete (S6), implementation initiated (S7), and implementation complete (S8). A completed implementation stage signifies a successful sale. In our logistic regression analysis, we use the log odds of winning the sale as our dependent variable. Our independent variables include the current total dollar amount, pipeline stages, new value of the pipeline, changes in pipeline status, customer emails, visits, phone calls, different territories, channel group dimension ID, and product group dimension ID.

In this logistic regression analysis [2], the goal is to understand what factors increase the likelihood of winning a sale, so the log odds of a successful sale outcome is used as the dependent variable [12]. The above independent variables are chosen since they represent critical aspects of the sales process and customer engagement that could influence the probability of a successful sale [23, 25]. Following are the reason of choosing each of these independent variables; first, current total dollar amount represents the financial value of each opportunity, which may correlate with the resources and attention dedicated to that opportunity, potentially impacting success rates [21, 24, 27]. Second, each pipeline stage indicates the position of an opportunity within the sales cycle, which likely affects its chances of closing; deals further along in the pipeline may have a higher probability of conversion. Third, new value of the pipeline reflects the recent change in potential revenue, which can indicate either growth or loss in interest or investment, potentially influencing the success probability [20]. Fourth, changes in pipeline status tracks movement through the pipeline, indicating the momentum of an opportunity, which may correlate with the likelihood of reaching a final sale. Fifth, customer emails, visits, and phone calls gauge the level of customer engagement [22]. Increased communication and contact are often associated with higher customer interest and trust, which can lead to a higher likelihood of closing the deal [19]. Sixth, geographic location can impact customer preferences, competition, and logistical factors, which can all influence sales outcomes. Seventh, channel group dimension ID represents the sales channel or pathway (e.g., direct sales, partners) through which the opportunity is pursued, as certain channels may be more effective for different types of deals [15]. Finally, different product groups can vary in their appeal, complexity, and relevance to certain customers, which can impact the probability of a successful sale. Including these variables allows for a comprehensive analysis of factors likely influencing the probability of winning a sale, helping to identify the most impactful aspects of the sales process [30]. The regression analysis reveals that only current total amount, pipeline stages, and total emails are statistically significant at the 1% level, while the other variables are not significant.

2. MOTIVATION:

Intelligent Medical Objects operates in the competitive market of electronic medical terminologies, with two primary business objectives: profit maximization and maximization of total sales. Attaining these objectives requires increasing the number of customers who successfully complete all stages of IMO's business pipeline. This pipeline consists of eight stages, each representing a critical progression point in the customer acquisition and engagement process. Only customers who advance through all eight stages ultimately convert to revenue-generating clients, as IMO can only issue invoices upon a customer's completion of the final stage. Failure to reach the eighth stage results in a lost sale, directly impacting both profit and sales volume. Given this, IMO aims to develop a predictive model to identify which factors most significantly impact a customer's likelihood of advancing through each pipeline stage. By pinpointing these critical variables, IMO can better understand and manage factors that contribute to customer retention and progression, ultimately aiming to increase the number of customers who reach the final pipeline stage and thus enhance overall profitability and sales outcomes.

In the pipeline literature, three primary forecasting methods are commonly discussed: weighted probability, specific account approach, and extrapolation. Weighted probability is calculated by multiplying the probability of close by the potential revenue from a customer, where potential refers to the total amount of anticipated invoices from that customer. Specific account approach focuses on a small number of accounts, with each account having one of two outcomes: *close* or *no close*. Given that our dataset includes over a thousand observations, this approach is impractical for our needs. Extrapolation applies when a structured sales model is consistently effective, making revenues highly predictable. This method takes an aggregate view of metrics such as total dollar amount and account count, projecting future values based on trends from the previous month. Since we lack a consistently effective sales model, this method is also unsuitable for our analysis. Furthermore, this type of analysis is very useful in cancer research [4, 6, 9–11, 34, 35]

We perform a logistic regression analysis using the log odds of the probability of securing a sales contract as our dependent variable. In this setup, there are eight stages within the business pipeline. If a customer reaches stage eight, we classify this as a win and assign a value of 1; otherwise, it is labeled a loss with a value of 0. The purpose of building this model is that, with a high log odds ratio for winning, there should be an increase in customers reaching stage eight. Consequently, more customers progress through the final stages of the pipeline [29]. For our independent variables, we include the current total amount, pipeline stages, the new value in the pipeline, status changes within the pipeline, total number of emails, customer visits, phone calls, territories, channel group dimension ID, and product group dimension ID [31].

3. DATA ANALYSIS:

The sources we are using for this analysis are tables built in IMO's Data Warehouse, *IDW*, notably

- ACTIVITY_PARTY_FACT: Total numbers of emails, visits and phone calls
- CHANNEL_SALES_FACT: Channel group dimensional ID, customer dimensions
- CUSTOMER_DIM: Territory Id
- PRODUCT_GROUP_DIM_ID: Product group ID
- TERRITORY_DIM_DIM_ID: Territory number
- MSCRM.ACCOUNT_ENTITY: Name of the customers
- MSCRM.OPPORTUNITY_AUDITDETAIL_ENTITY: Old pipeline status value, new pipeline status value
- MSCRM.OPPORTUNITY_AUDIT_ENTITY: Action name, creation date
- MSCRM.OPPORTUNITY_ENTITY: Current state, current pipeline status, current total dollar amount of IMO products, action name, current opportunity status, opportunity ID, account ID, opportunity status code

3.1. Data structure: To identify the most promising opportunities for analysis, we first need to narrow down the list from all available opportunities in Microsoft CRM. Currently, there are 28,025 unique customers in the MSCRM opportunity pipeline, with many of these customers having multiple opportunities. Some of these customers are existing IMO clients, and their opportunities involve new IMO products. The main reasons are as follows. First, with 28,025 customers in the pipeline, analyzing each opportunity would be time-consuming and overwhelming. By selecting only the most promising or relevant opportunities, we can focus on cases that are likely to yield significant insights. Second, by reducing the number of opportunities we make better use of resources such as time, budget, and analytical capacity. This helps us allocate resources to high-potential cases rather than spreading them across the entire pool. Finally, many customers have multiple opportunities, and some are already familiar with IMO products through previous products. By prioritizing opportunities for new IMO products or focusing on loyal customers, we can strategically target areas with a higher likelihood of success or growth potential.

Since interactions (such as calls, emails, and visits) with current customers may involve topics unrelated to a specific opportunity, we decided to focus on customers who have only one opportunity. This way, we can assume all activities are related to that opportunity, allowing us to analyze how these interactions impact progression through the pipeline. Out of the 28,025 customers in the opportunity pipeline, 174 have a single opportunity and are beyond the initial S-0 pipeline status. We excluded customers at S-0 because they have not yet shown any movement in the pipeline, and our goal is to analyze factors that influence progression. The 174 customers with a single opportunity had a total of 4,728 activities. In analyzing the impact of activities on pipeline

movement, it became apparent that most pipeline changes occurred on just one day. Only 24 customers had pipeline status changes that took place over multiple days.

The reasons for this include: first, pipeline statuses may be updated in bulk rather than gradually, so changes for a customer often occur in a single session or day [14, 32]. Second, key events or decisions, like contract signings or demos, can prompt immediate status changes without incremental updates. Third, status updates might only be logged once a final decision is reached, so the pipeline status reflects only the outcome rather than ongoing activities. Lastly, sales teams might focus on high-potential opportunities, concentrating their efforts on a single day to drive the opportunity forward [33]. These factors indicate that activities often cluster around critical points of change, meaning day-by-day analysis may not fully capture their impact on pipeline progression.

In R, a matrix was generated to assess the correlation between three variables: Current Pipeline Status, Total Activity, and Total Days in Pipeline. Current Pipeline Status represents the numerical status assigned to each customer in the pipeline [28]. Total Activity is the combined number of all phone calls, emails, and visits made while the customer was in the pipeline. Total Days in Pipeline reflects the total number of days the customer has spent in the pipeline. The results are shown below.

TABLE 1. Correlation Matrix

	Current pipeline status	Total activity	Total days in pipeline
Current pipeline status	1		
Total activity	0.1236959	1	
Total days in pipeline	0.2543786	-0.01152157	1

The matrix (1) shows that there is no significant correlation between these three variables.

3.2. Variable selection: In our logistic regression analysis, we use the log odds of securing a sales contract as the dependent variable. This choice stems from the fact that a higher log odds ratio reflects a greater number of customers advancing to the later stages of the sales pipeline, which aligns with our analysis goal [1]. We assign the current variable a value of either 0 or 1, where 1 indicates the contract has been won. Therefore, our objective is to have more instances of 1 than 0 in the results. Let Y be a binary response with probabilities $P(Y = 1|X = x) = p(x)$ and $P(Y = 0|X = x) = 1 - p(x)$. The probability density function can be written as

$$f_{Y|X}(y|x) = [p(x)]^y [1 - p(x)]^{1-y} = \exp \left\{ y\lambda(x) - \ln [1 + \exp\{\lambda(x)\}] \right\},$$

such that $\lambda(x) = \ln\{p(x)/[1 - p(x)]\}$ is the *logit* function. This is a special case of penalized likelihood [5]. Figure 1 provides a simulation of a logistic regression where the red lines stand for upper and lower 95% confidence intervals, respectively.

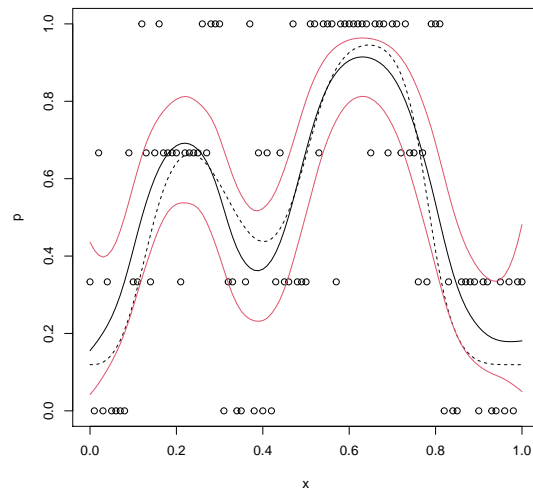


FIGURE 1. Simulation of a logistic regression.

Having a higher number of 1s is crucial for our analysis as it helps identify the factors that influence the success of winning sales contracts. First, by concentrating on instances where contracts are won (1s), the model can better understand the key drivers of success in the sales pipeline. This understanding aids in predicting and replicating those factors that lead to favorable outcomes. Second, the aim of the analysis is to move more customers to the later stages of the pipeline, and having more 1s allows us to pinpoint the characteristics that distinguish successful cases. This focus helps in identifying the variables most associated with pipeline progression. Lastly, a higher frequency of 1s strengthens the model's ability to predict future contract wins [26]. Since logistic regression relies on patterns in the outcome variable, a larger number of positive outcomes allows the model to learn and generalize more effectively. Ultimately, a greater number of 1s enables a more focused analysis of the success factors, making the findings more actionable for achieving business objectives.

The first independent variable we consider is *current total dollar amount*, which represents the value of IMO products ordered by a customer. A higher value indicates that the customer has placed a larger order, leading to a higher invoice. Another possibility is that the customer is particularly large, such as a large hospital or clinic. If more of these large customers are placing substantial orders, it could suggest that IMO products have gained a solid reputation, encouraging more customers to make purchases. This, in turn, could result in a greater number of customers advancing to the later stages of the pipeline. The second variable we use is pipeline status. As mentioned earlier, there are eight stages, and we assign a number from 1 to 8 to represent each stage. The main reason for including this variable is that a customer in a higher pipeline stage has

a greater likelihood of winning the contract compared to a customer in a lower stage. Consequently, the movement of this variable and the dependent variable follow the same direction.

The third independent variable we use is new *pipeline status* value, which represents the current position of a customer in the business pipeline. A customer in a higher stage of the pipeline is more likely to win the contract. We also consider *difference in status* as an independent variable, which is the change between the new and old pipeline status values. A larger difference indicates that a customer is progressing quickly through the pipeline. Moreover, a greater difference in status is associated with a higher probability of winning the contract. The next independent variables we consider are three types of customer activities: *email*, *visits*, and *phone calls*. An increase in the total number of any of these activities suggests that the customer may be more interested in IMO products, which could ultimately lead to winning the contract. Of these three activities, email is the least costly and most time-efficient, as visits may incur additional transportation expenses, and phone calls can involve waiting times or situations where the business executive may not answer [18]. In contrast, emails do not have these limitations. Later in this report, we will demonstrate that emails are actually the most significant activity of the three.

The last three independent variables we examine are *territory ID*, *Channel group dimensional ID*, and *product group ID*. The primary reason for including territory ID is to assess whether location plays an important role. For instance, if a customer is located far away, visiting them would be costly. However, if the customer is nearby, visits are more feasible. If the customer frequently uses the Internet, location may not be as significant. In our analysis, we found that location does not have a significant impact on winning the business contract. Lastly, we explore whether the channel, IMO products, or both are factors that influence the likelihood of securing a sales contract.

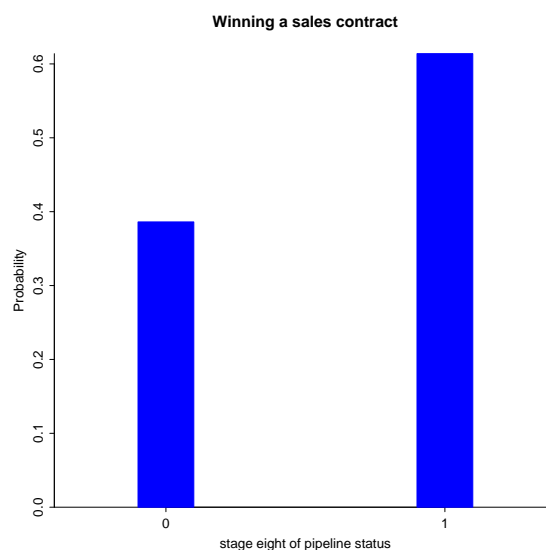
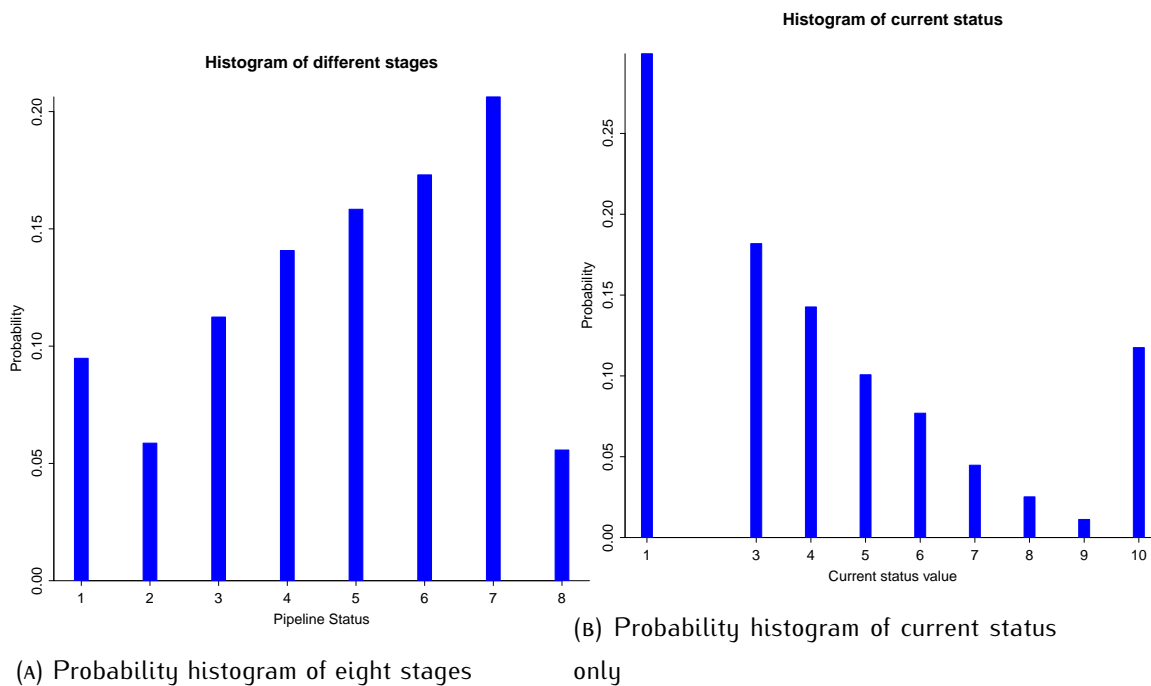


FIGURE 2. In horizontal axis 1 stands for the contract has been won, 0 otherwise.

Since we use the probability of winning the contract as the main dependent variable in our logistic regression, we assign the values 1 and 0 to current status to indicate whether the contract was won or not. For the independent variables, such as *opportunity status code*, *old pipeline status value*, *new pipeline status value*, *channel group dimensional ID*, and *product group ID*, we assign numerical values starting from 1, creating a set of categorical variables. To obtain the total number of emails, we first construct a set of categorical variables with values 0 and 1 for activity type, focusing on the specific category of email. We then sum all the 1s in this category. Similarly, we compute the total number of visits and phone calls using the same method.

In Figure (2), we show the probability of a customer winning the business contract compared to being in any other stage of the pipeline. The chance of winning the contract is nearly 60%, while the probability of being in any status other than *won* is around 40%. This clearly shows that less than 40% of the customers in the pipeline fail to reach the final stage. This is positive for IMO, as it indicates a higher proportion of customers are successfully completing contracts, which could lead to increased revenue from selling IMO products.

FIGURE 3. Histograms of all and current stages of business pipeline status



In the previous section, we examined the behavior of the dependent variable without considering the effects of the explanatory variables in our logistic regression. Now, we will explore the explanatory variables and discuss how they influence the probability of winning the business contract. In Figure 3, we present the probability histogram for two key explanatory variables: different stages of the opportunity pipeline and current status (referred to as the “new value code” in the data) of

the customer in the pipeline. The vertical axis represents the probabilities, which correspond to the relative frequencies.

If we focus on panel (4a) of Figure (3), we observe that the probability at stage 1 is around 0.10, and it decreases to 0.059 at the second stage. This makes sense, as after initial engagement, some customers may not continue, leading to a higher rejection rate, especially given that the total number of customers in this stage is the highest. The probability begins to increase as we move through the stages, peaking at 0.20 in stage seven (i.e., implementation initiated). However, at the final stage (i.e., implementation complete), the probability drops to around 0.05, which is very similar to the probability value of stage two.

In contrast, panel (4b) of Figure (3) clearly shows a declining trend in the probability of various pipeline statuses until stage nine, after which it abruptly increases to 0.125. This value is nearly the same as that of stage four in the pipeline status. Comparing these two panels of Figure (3), we observe two different trends: over time, the probability of different statuses increases, whereas in the current time period, the probability trend is rising. These results move in opposite directions. To further investigate this issue, we examine the difference between the previous and current statuses of a customer in the business pipeline, as shown in Figure (5).

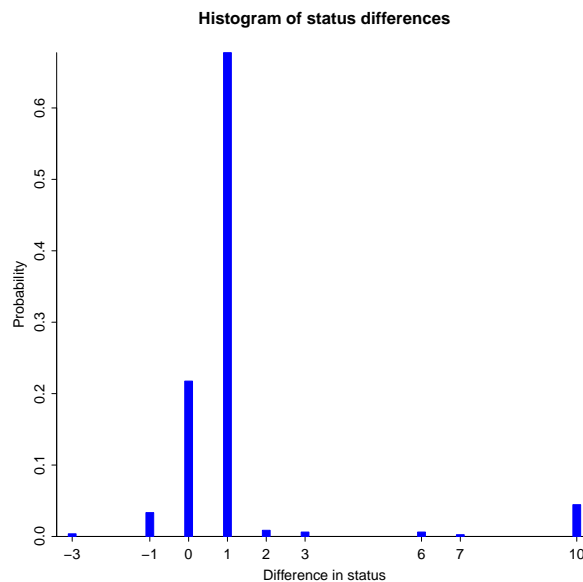
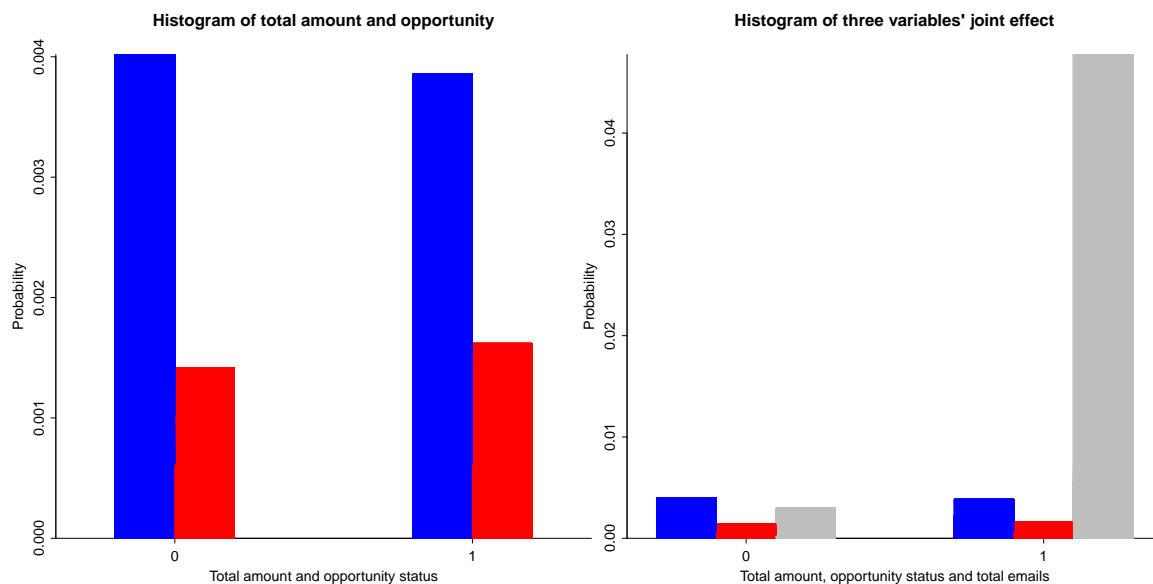


FIGURE 5. Difference in status with probabilities; negative values represent customers' backward movement.

In Figure (5), the horizontal axis represents the differences in status, while the vertical axis shows the corresponding probabilities. The status difference is obtained by subtracting the *old value code* from the *new value code*, where these two codes represent the previous and current statuses. We observe that a status difference of 1 has the highest probability, close to 0.7, indicating that existing

customers are most likely to move one step forward in the business pipeline. The second highest probability, around 0.24, corresponds to staying in the same status (i.e., a difference of zero). This suggests that most IMO customers are risk averse, preferring to remain at the same stage or progress only slightly rather than finalizing a sales contract. The status difference of 10 shows the third highest probability, around 0.05. Additionally, there are very low probabilities for backward movement, corresponding to differences of -3 and -1 , which indicates that a small proportion of customers have moved three stages backward. However, a one-step backward movement is more likely than a three-step backward movement, as evidenced in the figure.

FIGURE 6. Histograms of effect of explanatory variables on winning the contract



(A) Dependent variable gets affected by total amount and opportunity status.

(B) When affected by total amount, opportunity status and total emails.

Finally, we want to discuss the effects of explanatory variables affect our primary dependent variable. In panel 7a of figure 6 we take only total amount and opportunity status in the business pipeline. Blue and red bars represent the effects corresponding to *total amount* and *opportunity status*, respectively. If we look carefully we observe that, both the variables have same effect of the winning probability sales pipeline. The effective probability from total amount is 0.004 whether the effective probability from *opportunity status* is lower. If we compare this result with figure 2 we can see different types of effects. In figure 2 the probability of winning (corresponding to 1) a contract is higher than the rest of the opportunity statuses while panel 7a indicates two important explanatory variables in our case have same effect in explaining winning of a contract. Moreover, adding the variable total number of emails like in panel 7b leads to more effectiveness of the third

variable. Apart from these three variables we are not able to find another variable which can explain the dependent variable.

From the analysis above, it appears that there may be other significant variables not present in the database. One factor that intuitively stands out is the communication skills of the salesperson. It is well-understood that a businessperson with poor communication skills is unlikely to succeed, while someone with a polite and modest demeanor can still thrive, even if their product is not the best [17]. In our case, one possible missing factor might be the years of experience of the sales executives. Another key factor could be the frequency with which IMO introduces new technologies in medical terminology. Currently, IMO is transitioning from *IMO1* to *IMO2*. While this new technology is more user-friendly, the challenge may arise on the consumer side. Implementation and training require time and resources, which could result in losing some customers due to the adoption of new technology. In the following sections, we will conduct more advanced statistical analysis to identify significant variables.

4. MODEL

In our case the dependent variable is current pipeline status. Furthermore, if the customer wins the sales deal then we give 1 and 0 otherwise. Therefore, in our case

$$\text{logit } p_j = \log_e o_j = \log_e \left(\frac{P_j(Y = 1)}{1 - P_j(Y = 1)} \right) = \mathbf{x}' \mathbf{f}_j, \quad \forall j = 1, 2, \dots, 1024 \quad (1)$$

where o_j is defined as *odds ratio*, $P_j(Y = 1)$ is the probability of j^{th} customer to win the sales contract, \mathbf{x} is a matrix of (11×1024) dimension and \mathbf{f}_j is a (11×1) vector of coefficients. The odds can vary on a scale of $(0, \infty)$, so the log odds can vary on the scale of $(-\infty, \infty)$. For a real valued explanatory variable x_{ij} , the intuition here is that a unit additive change in the value of the variable should change the odds by a constant multiplicative amount. Exponentiating, the equation (1) is equivalent to,

$$e^{\text{logit } p_j} = e^{\beta_0 + \beta_1 x_{1j} + \beta_2 x_{2j} + \dots + \beta_{10} x_{10j}}, \quad \forall j = 1, 2, \dots, 1024$$

$$o_j = \frac{P_j}{1 - P_j} = e^{\beta_0} e^{\beta_1 x_{1j}} e^{\beta_2 x_{2j}} e^{\beta_3 x_{3j}} \dots e^{\beta_{10} x_{10j}}, \quad \forall j = 1, 2, \dots, 1024. \quad (2)$$

We can convert freely between probability P_j and odds o_j for an event of the j^{th} customer versus its complement as $o_j = P_j (1 - P_j)^{-1}$ and $P_j = o_j (o_j + 1)^{-1}$. We also know that the *inverse* of the *logit* function is *logistic* function.

The odds ratio in equation (2) represents the likelihood of an event occurring when only two outcomes are considered. For the j^{th} customer, the probability of winning a contract is denoted as P_j or $P_j(Y = 1)$. Conversely, $1 - P_j(Y = 1)$ represents the probability of losing the contract. If $o_j < 1$, then losing the contract (i.e., $1 - P_j(Y = 1)$) is more likely. If $o_j > 1$, then winning the contract (i.e., $P_j(Y = 1)$) is more likely. Lastly, if $o_j = 1$, then winning and losing the contract

are equally likely. In essence, the odds ratio reflects how the odds of an event change based on another factor, specifically by comparing the odds in one scenario to those in a different scenario.

The inverse of the logit function is logistic function. For j^{th} individual customer if $logit(P_j) = z_j$, then

$$P_j = \frac{e^{z_j}}{1 + e^{z_j}}.$$

The logistic function will map any value of the right hand side (z_j) to a proportional value between 0 and 1. The explanatory variables used in the logistic regression is as follows:

- x_{1j} = Current total amount of IMO products
- x_{2j} = Current opportunity status
- x_{3j} = New pipeline status value
- x_{4j} = Difference in pipeline status (obtained by subtracting old pipeline status value from new value)
- x_{5j} = Total number of emails
- x_{6j} = Total number of visits
- x_{7j} = Total number of phone calls
- x_{8j} = Territory number
- x_{9j} = Channel group dimensional ID and,
- x_{10j} = Product group ID

Since the dependent variable is the natural logarithm of the odds, the interpretation of each component differs from that in simple linear regression. For instance, the interpretation of β_{1j} is that if the current total amount increases by one unit, the natural log of the odds will change by β_{1j} units.

5. RESULTS:

In this section, we discuss the results from the logistic regression. P-values highlighted in bold in table (2) represent explanatory variables that are significant at the 0.001 level. Out of the ten explanatory variables, Current total amount of IMO products, new pipeline status value, and total number of phone calls are negatively correlated with the natural log of the odds of winning the sales contract. Notably, Current total amount of IMO products is significant at the 0.1% level, which is surprising. This suggests that customers with larger order volumes are less likely to have favorable log odds of winning the sales contract. One possible explanation is that they may prefer to focus on larger companies rather than IMO. This implies that customers with smaller sales volumes are more likely to progress through all eight pipeline stages. Although new pipeline status value and total number of phone calls also have negative coefficients, they are not significant at the 0.01% level.

In table (2), we observe that only current total amount of IMO products, current opportunity status, and total number of emails are significant at the 0.001 level. Both current opportunity status and total number of emails have positive coefficients in explaining the log odds of winning the sales contract. The positive significance of current opportunity status indicates that as a customer progresses to higher stages in the pipeline, their probability of winning the sales contract increases significantly. This means, for example, that a customer at stage 7 is more likely to finalize the contract than a customer at stage 4.

Total number of emails is another positively significant explanatory variable. This suggests that the more a customer emails, the more likely they are to complete all the stages of the business pipeline. It is the only activity type that shows significance. One possible reason for this could be that when a customer emails IMO, the sales executive typically responds with helpful links that provide detailed information about current activities. In contrast, if the customer were to call IMO, the information might not be as clear or detailed as it would be through email.

TABLE 2. Logistic regression results

Coefficients	Estimated value ($\hat{\beta}$)	Standard error	P-value
Intercept	-6.7470	0.9259	3.19×10^{-13}
Current total amount of IMO products	-2.912×10^{-5}	6.446×10^{-6}	6.27×10^{-6}
Current opportunity status	1.2440	0.1218	$< 2 \times 10^{-16}$
New pipeline status value	-9.997×10^{-2}	7.865×10^{-2}	0.2037
Difference in pipeline	-0.1420	0.2446	0.5616
Total number of emails	0.01397	2.343×10^{-3}	2.51×10^{-9}
Total number of visits	0.04311	0.02932	0.1415
Total number of phone calls	-0.05183	0.07644	0.4977
Territory number	1.861×10^{-3}	9.767×10^{-4}	0.0567
Channel group dim ID	0.0183	0.05686	0.7476
Product group ID	0.0874	0.04789	0.0678

Finally, the insignificance of total number of visits helps explain the significance of total number of emails. Frequent visits incur higher transportation costs, which become more significant if the customer lives far from IMO. In this case, the customer is more likely to prefer emailing rather than visiting in person. The lack of significance of total number of visits further suggests that location plays a role in explaining the log odds of winning the sales contract. Another supporting piece of evidence is the insignificance of territory number.

6. DISCUSSIONS:

The biggest challenge in this project is the lack of knowledge about MSCRM. Analyzing the data often raises more questions than it answers. The process by which a customer moves through the pipeline and how these movements are logged is unclear. In some instances, customers exhibit backward movement, and it is impossible to determine if this is valid or not. Additionally, there are instances where a customer's pipeline status is set to null. There is no documentation explaining what a null pipeline status means or why a customer would have one. Furthermore, there are instances where customers seem to skip levels, showing a status higher than their previous one without any evidence that they went through the intervening stages. Another issue is that the pipeline status dimension table contains two values for each status, with no explanation for the multiple options.

These problems with pipeline movement are compounded by the fact that most movements are recorded on a single date for each customer. Like the previous issue, there is no documentation explaining why this occurs, which raises doubts about the accuracy of the data or whether all movements are incorrectly attributed to one date. With only one date per customer, linking activity dates to pipeline movement dates becomes very challenging. More accurate analysis of pipeline movement would be possible with finer-grained date tracking.

When linking activities to pipeline movements, it appears that most movements are either random or driven by factors unrelated to the documented activities in CRM. The sample size used in this project was small, so a next step could involve analyzing whether there is any relationship between activity and pipeline movement when considering the entire customer base in the opportunity pipeline.

To advance this project, further research into MSCRM and how data is transferred to the SQL servers is necessary. Sometimes, it seems that certain information is not correctly logged into SQL, or if the data is correct, it is difficult to interpret. Adding more variables to the dataset could improve the analysis, such as demographic information (territory, number of beds, number of clinicians, etc.), details about the salesperson, or additional MSCRM variables that we do not yet have definitions for but may significantly affect pipeline movement.

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