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| RESEARCH ARTICLE

Predicting Donor Churn and Customer Sentiment from Reviews Using Logistic Regression and NLP: A Data-Driven Approach to Retention and Sentiment Analysis

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| ABSTRACT

This study employs a dual-analytical approach to explore donor churn prediction and customer sentiment analysis using logistic regression and natural language processing (NLP). Drawing on a dataset of 2,000 donors from a non-profit organization (2012–2017), we use logistic regression to identify key determinants of donor attrition, including direct marketing, TV and Facebook advertising, publicity, and demographic variables. Our best-performing churn model achieved an AUC of 0.8629, highlighting the value of personalized direct marketing and demographic segmentation in donor retention strategies. In parallel, we analyze 2,500 Amazon magazine subscription reviews using sentiment analysis and Latent Dirichlet Allocation (LDA) topic modeling. Despite accounting for negativity bias, most reviews reflected positive sentiment. Six key themes emerged from topic modeling, including lifestyle, technology, and delivery concerns, offering actionable insights for consumer engagement and product improvement. By integrating quantitative and textual data, this research provides a data-driven framework for improving donor retention and understanding customer sentiment. These findings offer strategic guidance for marketing, fundraising, and review-based customer analytics in both nonprofit and commercial sectors.

| KEYWORDS

Donor Churn; Customer Sentiment; Logistic Regression; Data-Driven Approach; Retention and Sentiment Analysis

| ARTICLE INFORMATION

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1. Introduction

In today's competitive and data-driven environment, understanding customer and donor behavior is vital for both for-profit and non-profit organizations. Donor attrition, or churn, poses a significant challenge for non-profits that rely on consistent support from individuals. Research suggests that proactive identification of churn-prone individuals can substantially improve retention efforts and maximize lifetime value (Schweidel & Knox, 2013). Alongside quantitative metrics, insights from textual data, such as online reviews, provide a rich source of unstructured information that can reveal underlying sentiments and motivations (Pang & Lee, 2008; Liu, 2012).

This paper adopts a two-fold analytical approach. First, we analyze a large dataset of donor behavior to identify the key determinants of donor churn using logistic regression. We evaluate how direct marketing efforts, advertising expenditures, and publicity influence the likelihood of churn. Secondly, we apply natural language processing (NLP) techniques—including sentiment analysis and Latent Dirichlet Allocation (LDA)—to Amazon product reviews in the magazine subscription category. This analysis uncovers the emotional tone and dominant themes expressed in customer feedback, enabling organizations to better understand consumer perceptions and needs.

Our study builds on existing literature in marketing science and text analytics. The role of direct marketing in enhancing customer loyalty and transaction frequency has been well documented (Schweidel & Knox, 2013). Similarly, the impact of social media engagement and brand interactions on customer retention has gained attention in recent years (Maecker, Barrot, & Becker, 2016). In the domain of text analysis, sentiment and topic modeling have proven effective in extracting structured insights from consumer-generated content (Blei, Ng, & Jordan, 2003; Liu, 2012).

By integrating statistical modeling with NLP techniques, this study provides a comprehensive understanding of churn drivers and consumer sentiment, offering strategic implications for donor retention, campaign effectiveness, and customer communication.

2. Literature Review

2.1 Donor Churn and Retention Analytics

Donor retention is a critical metric in the sustainability of non-profit organizations. Churn, defined as the cessation of support by a donor, often results in significant revenue losses and increased acquisition costs. Several studies have explored predictive modeling to identify at-risk customers or donors. Schweidel and Knox (2013) emphasized the importance of incorporating direct marketing activities into latent attrition models, finding that increased direct communication reduced the probability of churn. Similarly, Reinartz and Kumar (2000) demonstrated that relational variables such as contact frequency, recency, and engagement history play a central role in predicting lifetime customer value and churn risk.

Direct marketing has consistently proven effective in enhancing donor loyalty. For instance, Kotler and Lee (2005) noted that personalized outreach strategies foster stronger donor relationships. However, other advertising channels show more ambiguous effects. While television advertisements may help build brand awareness and long-term loyalty (Ngoc Khuong et al., 2016), their effectiveness in targeted retention is limited due to their broad reach and high cost. On the other hand, digital platforms, especially social media, offer cost-effective personalization. Maecker, Barrot, and Becker (2016) found that brand-consumer interactions on platforms like Facebook improved retention by facilitating two-way communication.

Moreover, measures such as Customer Lifetime Value (CLV) have been widely adopted to guide marketing resource allocation. Blattberg, Getz, and Thomas (2001) argued that integrating churn probabilities with profit estimation can help organizations prioritize high-value donors for retention campaigns.

2.2 Sentiment Analysis and Text Mining

In the digital era, unstructured textual data—such as online reviews, social media comments, and survey responses—have become valuable sources of consumer insight. Sentiment analysis, a key component of text mining, involves the classification of opinions as positive, negative, or neutral. Pang and Lee (2008) and Liu (2012) emphasized that lexicon-based methods (e.g., Bing or AFINN lexicons) are widely used to compute sentiment polarity. These methods have shown reliable performance in understanding brand perception and user satisfaction.

To enhance interpretation, some models introduce sentiment weighting to account for phenomena like negativity bias—where consumers give more weight to negative experiences (Baumeister et al., 2001). This is especially useful in product categories where emotional response plays a major role in evaluation.

Topic modeling, especially Latent Dirichlet Allocation (LDA), enables unsupervised extraction of themes from large text corpora. Blei, Ng, and Jordan (2003) introduced LDA as a generative model capable of identifying abstract topics based on word co-occurrence. This technique has been successfully applied in marketing, journalism, and health research to uncover latent structures in text (Steyvers & Griffiths, 2007).

Combined with sentiment analysis, topic modeling provides a comprehensive view of customer discourse, revealing not only how consumers feel but also what they talk about. For example, Tirunillai and Tellis (2014) found that topic-sentiment mapping of online reviews could predict product sales and identify emerging trends.

2.3 Integration of Quantitative and Textual Methods

Recent studies have begun integrating structured data (e.g., demographics, transaction history) with unstructured textual analysis to improve customer insight. (Blei, Ng, & Jordan, 2003; Liu, 2012) advocate for hybrid models that utilize both numerical and text features to better predict customer behavior, such as churn or repurchase intent. This interdisciplinary approach allows organizations to make more holistic and informed strategic decisions. A similar approach has been observed in forecasting problems, where structured SCADA data is combined with machine learning and time series techniques to enhance predictive accuracy, as demonstrated by Alam and Mozomder (2025) in their comparative analysis of wind power output prediction.

3. Methodology

This study employs a mixed-methods approach to investigate the determinants of donor churn and to extract actionable insights from online textual reviews. The methodology is structured into two main components: (1) donor churn prediction using logistic regression and customer lifetime value estimation, and (2) sentiment and topic analysis on consumer reviews using natural language processing (NLP) techniques.

The first component focuses on building a statistical model to predict the probability of donor churn. The donor dataset comprises 31,929 observations across 15 variables, with 2,000 unique donors tracked over a five-year period (2012–2017). Initial data cleaning involved handling character-to-numeric conversions for variables like television and Facebook advertising expenditures. Variables such as direct marketing contacts (DM), TV and Facebook advertising, and publicity efforts were selected as independent variables, while the binary variable churnD served as the dependent outcome. Demographic variables such as age, gender, household size, income, and relationship length were later introduced for expanded modeling.

To guide the regression analysis, the study proposed four hypotheses: H1, that increased direct contact via DM reduces the probability of donor churn; H2, that television advertising has no significant impact on donor churn; H3, that increased Facebook advertising reduces churn probability; and H4, that publicity has no significant effect on donor retention. Exploratory data analysis revealed that the average donor relationship length was approximately 15 months, with a median of only 2 months and a mode of 1 month—indicating a high early-dropout rate. Demographically, the sample included 923 female and 1,077 male donors.

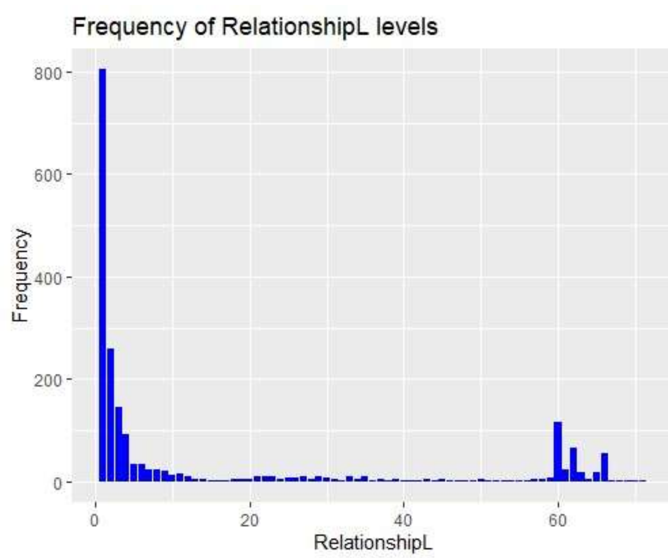

Figure 1: Histogram showing the skewed distribution of relationship length

We can see from figure 1 that the majority of the donors had relatively short rela1onship 1mes. In this sense the data is right skewed. Most of the donors donated for a period of less than 10 months. To make this graph, we summarized the data for unique customer IDs and found the length of relationship for each of the 2000 donors. Following this, it was easy for us to calculate the accurate mean, median, and mode for the data. The mean length of rela1onship is **14.96** months. The median length of the relationship is **2** months. The modal length of a relationship is **1** month.

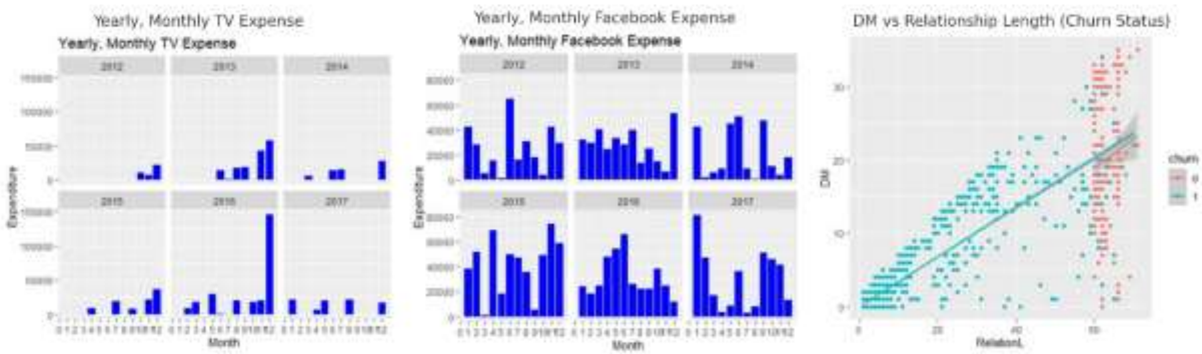

Figure 2: Advertising Expenditure Trends and Donor Engagement Dynamics

Figure 2 presents a visual summary of three key aspects of the donor dataset. The first panel illustrates **Yearly and Monthly Television Advertising Expenditure** from 2012 to 2017. The data shows that television ad spending typically increased toward the end of each year, with the exception of 2017, where expenditures were more evenly distributed throughout the months. This confirms that advertising expenditures were consistently structured across customers, independent of individual donor characteristics.

The second panel displays **Yearly and Monthly Facebook Advertising Expenditure** over the same period. Unlike television advertising, Facebook ad spending patterns varied significantly from year to year and month to month, indicating the absence of a systematic allocation schedule. Similar to the TV ad data, this plot reinforces the observation that monthly and yearly advertising budgets were uniformly applied across all donors.

The third panel visualizes the relationship between **Direct Marketing Contact Frequency**, **Length of Donor Relationship**, and **Churn Outcome**. A positive correlation is observed between the number of direct mail contacts and the duration of the donor relationship. Donors who received more direct outreach tended to stay engaged longer, with churned donors (in red) clustering toward shorter relationship lengths and lower contact frequencies. This pattern supports the hypothesis that increased direct marketing is associated with stronger donor retention.

Logistic regression was implemented using R's glm() function with a binomial family and a logit link. An initial model (Model A) was estimated using a 70:30 training-test split to evaluate performance on unseen data, while Model B used the full dataset for comprehensive estimation. The base model with four predictors (DM, TV_Adv, Facebook_Adv, and Publicity) returned a McFadden's R^2 of 0.06, an AIC of 8894.44, and an AUC of 0.6866. Notably, the model demonstrated high specificity (0.898) but low sensitivity (0.303) at the default 0.5 threshold. Adjusting the threshold to 0.15 improved classification balance.

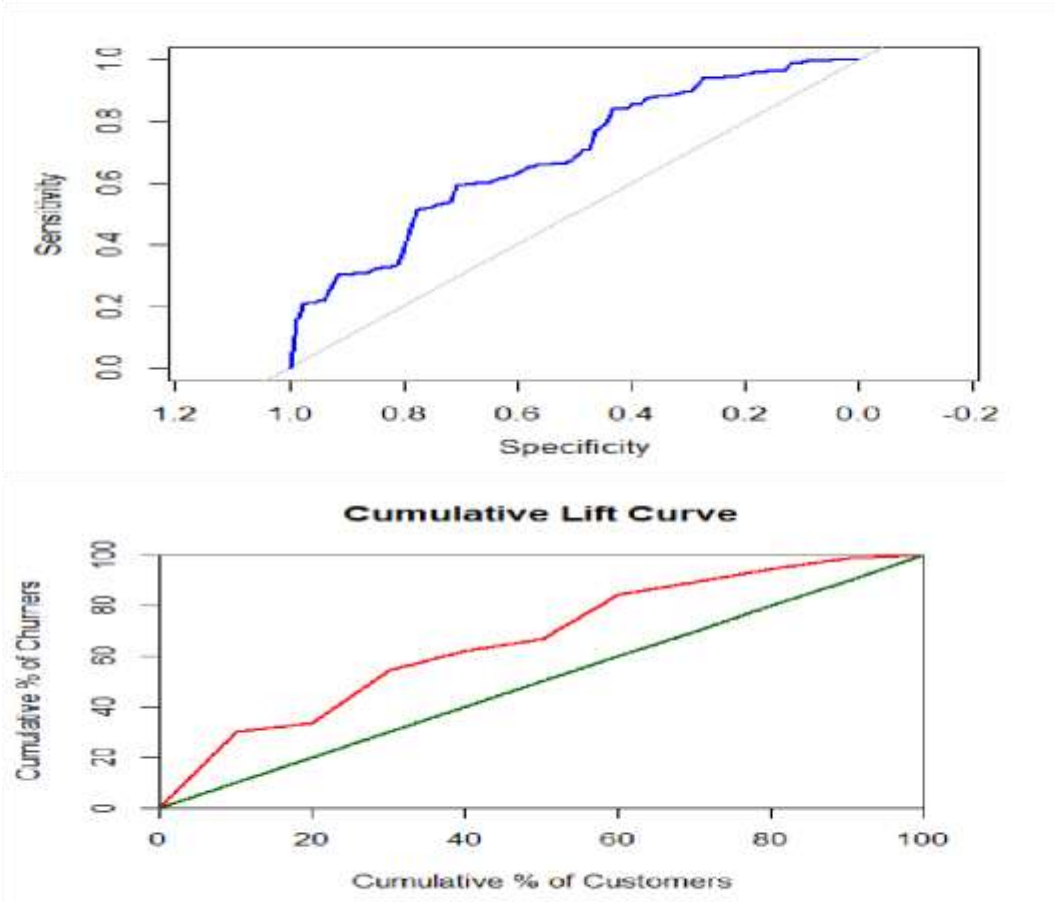

Figure 3: ROC curve for Model A

Model diagnostics led to the development of multiple alternative models: one excluding DM, another excluding Publicity, and a third including only TV and Facebook advertising. These were compared on performance metrics including AIC, specificity, sensitivity, and AUC. The final and most robust model was selected via stepwise variable reduction using stepAIC(), incorporating demographic and behavioral features such as age, gender, household size, website visits, and relationship length. This optimized model achieved a McFadden's R^2 of 0.19, an AUC of 0.8629, and a significantly improved sensitivity of 0.674.

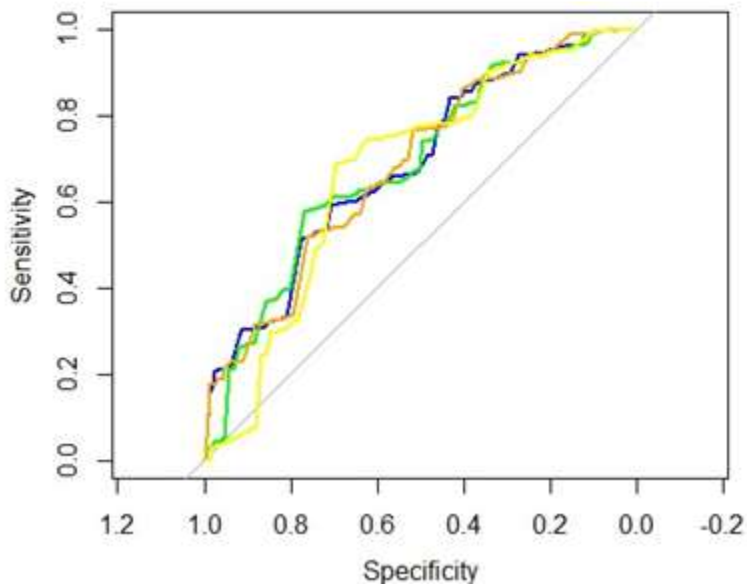

Figure 4: ROC curve comparing all model variants

Additionally, Customer Lifetime Value (CLV) was estimated for individual donors based on churn probabilities and monthly donation rates. Under assumptions of €3 and €5 monthly contributions, the CLVs were €142.3 and €249.7 respectively. The marginal cost of donor retention through DM was subtracted to yield a positive net benefit in both scenarios, justifying retention investments.

The second component of the study focuses on textual analysis of consumer reviews from Amazon's Magazine Subscription category. A total of 2,500 reviews were analyzed. The text was preprocessed by converting all content to lowercase and removing numbers, punctuation, common stopwords, and domain-specific irrelevant words. Lemmatization was applied using the textstem package to consolidate word forms. Frequency analysis was conducted pre- and post-cleaning to assess vocabulary reduction and clarity.

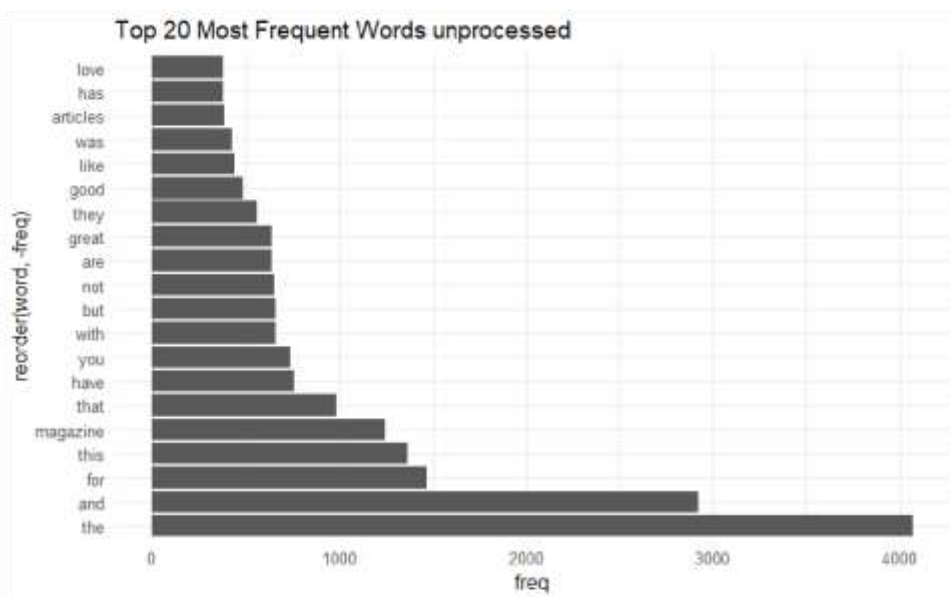

Figure 5: Bar plot of most frequent words before preprocessing

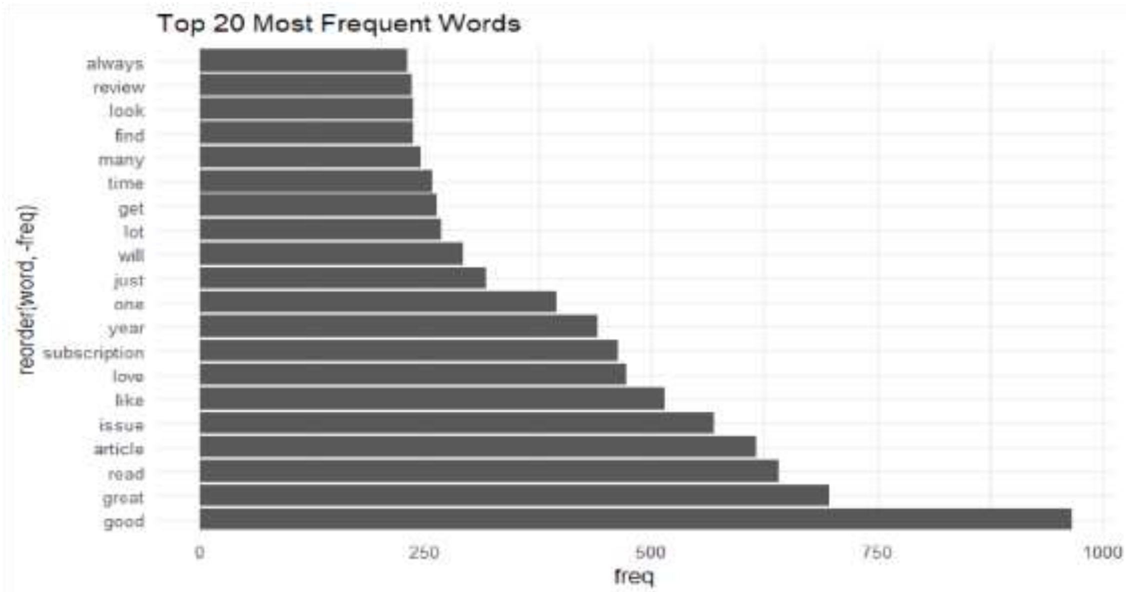

Figure 6: Bar plot of most frequent words after preprocessing

For sentiment analysis, we employed the Bing lexicon and introduced a negativity bias by weighting negative words twice as heavily as positive ones. This adjustment was intended to reflect the stronger psychological impact of negative experiences. The sentiment score for each review was computed using a normalized formula:

$$(W_{pos} - 2W_{neg})/(W_{pos} + 2W_{neg})$$

This score ranged from -1 (strongly negative) to +1 (strongly positive). Results indicated that most reviews had a positive sentiment despite the negativity adjustment.

Finally, we applied Latent Dirichlet Allocation (LDA) for topic modeling. The optimal number of topics (K=6) was selected based on a scree plot and perplexity score analysis. The six identified topics included: (1) Lifestyle and Beauty, (2) Tech and Reviews, (3) Project and Ideas, (4) Reading and E-Books, (5) Subscription and Delivery, and (6) Men's Health. Each topic was labeled based on its top-weighted terms.

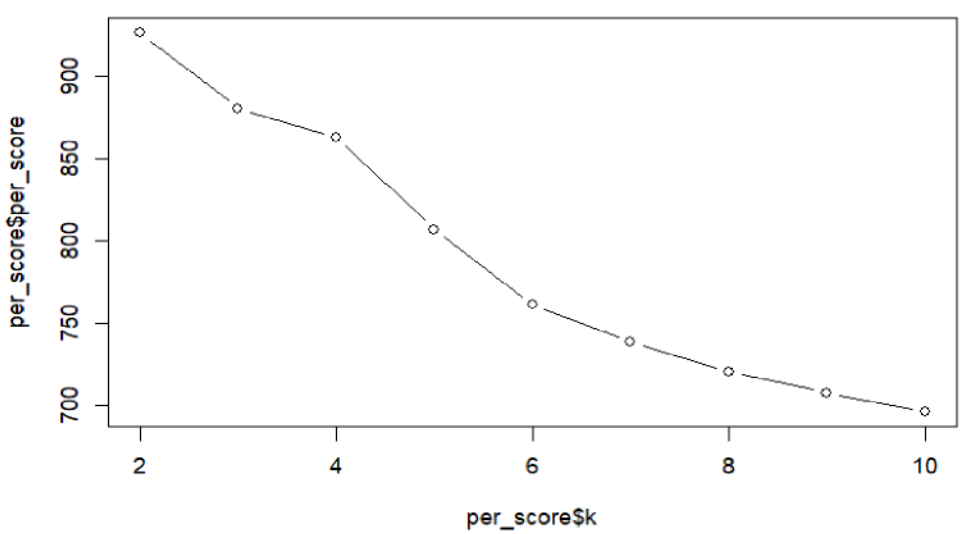

Figure 7: Scree plot with optimal number of topics

k <int>	per_score <dbl>
2	926.2362
3	880.6535
4	862.8394
5	807.2838
6	761.2067
7	738.8344
8	720.6416
9	708.0654
10	696.1999

Table 1: Topic labels with top words

In sum, this integrated methodology allowed us to combine predictive modeling and NLP to offer a comprehensive view of churn dynamics and customer sentiment. The next section presents detailed results and managerial implications derived from this analysis.

4. Results and Discussion

4.1 Donor Churn Model Results

The initial logistic regression model (Model A), which included four predictors—Direct Marketing (DM), Television Advertising (TV_Adv), Facebook Advertising (Facebook_Adv), and Publicity—offered modest explanatory power. It achieved a McFadden's R^2 of 0.06 and a Cragg-Uhler R^2 of 0.07, indicating limited variance explanation. However, all four predictors were statistically significant ($p < 0.05$). The DM variable had an odds ratio of 0.77, meaning that a one-unit increase in direct contact decreased the probability of churn by 23%, thereby supporting **Hypothesis 1**. Conversely, TV and Facebook advertising each showed negligible effects with odds ratios close to 1, suggesting they have little impact on churn, confirming **Hypothesis 2** and **Hypothesis 3** respectively. Publicity also had a small but statistically significant negative impact on churn (odds ratio ~0.97), which partially contradicts **Hypothesis 4**, indicating a slight retention effect from publicity.

Model A's classification performance revealed high specificity (0.898) but relatively low sensitivity (0.303), meaning it was more effective at identifying donors who did not churn than those who did. The model's AUC of 0.6866 indicates moderate predictive capability. To improve model performance, threshold tuning was performed (adjusted to 0.15), which improved sensitivity but with a slight trade-off in specificity.

Metric	**No DM & No Publicity**	**Publicity**	**DM**	**OG Model**
McFadden's R^2	0.04	0.05	0.04	0.19
AIC	9017.94	8997.06	9041.99	8894.44
BIC	9041.99	9029.11	8934.51	8934.51
AUC	0.946	0.872	0.866	0.8629
Sensitivity	0.23	0.684	0.303	0.674
Specificity	1	0.975	0.898	0.853
Hit-Rate	0.045	0.06	0.04	0.91
Null Deviance	9410.6	9410.6	9410.6	9410.6
LR-Test	Significant	Significant	Significant	Significant

Table 2: Comparison of Logistic Regression Models for Donor Churn Prediction

Subsequent model comparisons highlighted that removing DM or publicity reduced predictive performance. The optimized model generated using stepwise AIC reduction included demographic and behavioral variables (e.g., gender, age, household size, income, relationship length, and website visits). This model significantly outperformed all others with a McFadden's R^2 of

0.19 and AUC of 0.8629. It also achieved a more balanced classification profile, with sensitivity increasing to 0.674 and specificity maintained at 0.853.

The interpretation of model coefficients provided practical insights. Male donors were found to be 29.2% less likely to churn, and each additional household member reduced churn likelihood by 10.6%. A one-month increase in relationship length lowered churn risk by 7.2%, and each additional DM contact decreased churn probability by 37.5%. These findings validate the importance of personalized outreach and segmentation in donor retention strategies.

4.2 Customer Lifetime Value (CLV) Analysis

Using the churn probabilities derived from the logistic model, CLV was calculated for two revenue scenarios: €3 and €5 monthly donations. In both cases, the estimated CLVs were positive (€142.3 and €249.7, respectively), even after subtracting direct marketing costs. These results support targeted retention efforts, particularly for donors predicted to churn but still demonstrating substantial future value. This also emphasizes the cost-efficiency of retention campaigns compared to acquiring new donors.

4.3 Sentiment Analysis and Text Mining

The sentiment analysis of 2,500 magazine subscription reviews revealed that the majority of reviewers expressed positive sentiment, even after adjusting for negativity bias. The average sentiment score skewed right on the -1 to +1 scale, indicating overall satisfaction in the product category. This finding contrasts with literature that often highlights consumer negativity bias in reviews (Baumeister et al., 2001)

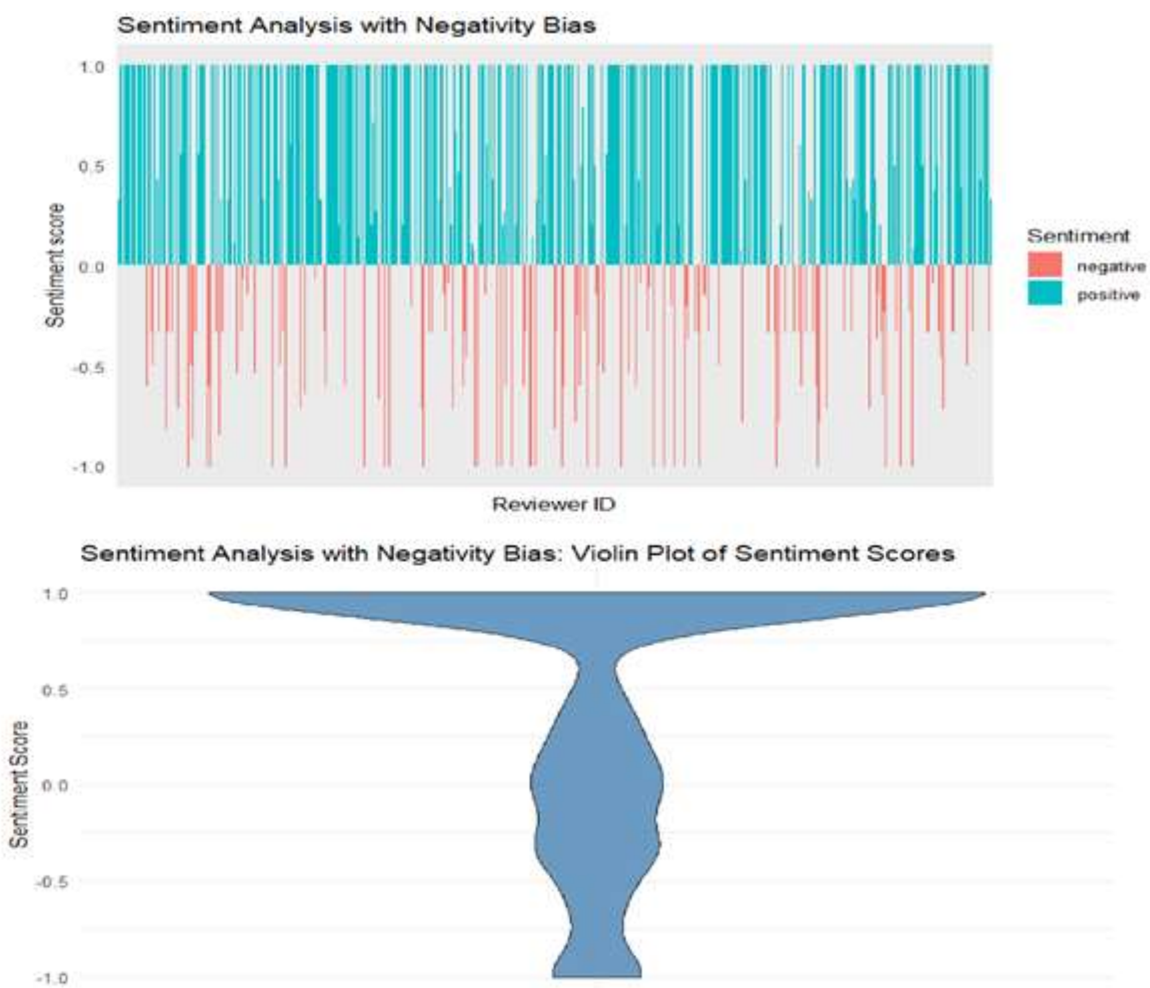

Figure 8: Sentiment score distribution plot

Topic modeling via Latent Dirichlet Allocation identified six coherent themes in the corpus. These topics included (1) Lifestyle and Beauty, (2) Tech and Reviews, (3) Project and Ideas, (4) Reading and E-Books, (5) Subscription and Delivery, and (6) Men's

Health. Most topics aligned with niche interests, suggesting strong product segmentation in this domain. The combination of topic and sentiment analysis presents an opportunity for businesses to tailor marketing strategies based on not just what customers are saying, but how they feel. For example, subscription and delivery issues were often associated with slightly negative sentiment, suggesting operational improvements could significantly impact satisfaction.

A tibble: 6 × 2

topic <int>	label <chr>
1	love, great, good, article, allure, read, glamour, beauty
2	good, computer, review, read, like, great, maximum, article
3	good, great, project, idea, lot, tip, read, many
4	read, kindle, good, mag, subscription, love, just, like
5	subscription, issue, receive, year, order, first, get, will
6	article, health, like, read, mens, good, page, man

Table 3: Topic-word matrix and associated sentiment

4.4 Managerial Implications

From a strategic standpoint, the results offer clear guidance for marketing managers in both non-profit and commercial sectors. First, direct marketing remains the most effective lever for donor retention, especially when personalized and targeted. Second, demographic segmentation—particularly by gender, age, and household size—can refine outreach strategies. Third, digital and TV advertising may have limited short-term effects on churn but could play a longer-term branding role.

In the context of review analytics, sentiment and topic modeling can be used not only for performance monitoring but also for product innovation and communication refinement. Organizations should focus on resolving logistics and delivery-related concerns while maintaining strong engagement around themes like content quality, tech usability, and personalization.

5. Conclusion and Recommendations

This study applied a dual-analytical approach to understand donor behavior and customer sentiment by integrating logistic regression, customer lifetime value modeling, and natural language processing techniques. Using a donor dataset from a non-profit organization, we identified key drivers of donor churn and found that direct marketing efforts significantly reduce the likelihood of churn. In contrast, advertising expenditures on TV and Facebook showed minimal impact on donor retention. Demographic features such as gender, household size, and relationship duration also proved important in refining churn predictions. Our best-performing model, generated via stepwise AIC selection, achieved a high AUC (0.8629) and demonstrated improved sensitivity and specificity, supporting the use of data-driven segmentation in donor outreach strategies.

Customer Lifetime Value (CLV) calculations reinforced the economic rationale for retaining churn-prone donors. Even under conservative revenue assumptions, retaining individual donors yielded positive net benefits, validating the cost-efficiency of targeted retention campaigns. These results are critical for budget-constrained non-profit organizations that must prioritize their outreach efforts for maximum impact.

In parallel, sentiment and topic analysis of 2,500 Amazon magazine subscription reviews revealed mostly positive customer sentiment, even when accounting for negativity bias. Topic modeling via LDA uncovered six distinct themes, providing actionable insights into consumer interests and preferences. This combination of sentiment and content analysis offers a richer understanding of consumer attitudes that can guide product design, communication strategies, and customer service improvements.

Based on our findings, we recommend the following:

1. **Prioritize Direct Marketing Campaigns:** Non-profits should invest more in direct and personalized outreach, as it significantly reduces churn and enhances donor loyalty.
2. **Segment Donors by Demographics and Behavior:** Age, gender, household size, and relationship length are valuable predictors of donor behavior and should inform campaign targeting.
3. **Use Churn Probabilities to Maximize CLV:** Incorporate predicted churn risk into CLV frameworks to prioritize high-value at-risk donors for retention spending.

4. **Refine Advertising Strategies:** Since TV and Facebook ads have limited immediate effects on retention, these should be used selectively for awareness and long-term brand positioning rather than short-term retention.
5. **Monitor Consumer Sentiment in Real Time:** For businesses, ongoing sentiment analysis of reviews and social media can act as an early warning system for service or product dissatisfaction.
6. **Leverage Topic Insights for Content and Product Development:** Understanding what customers talk about most frequently allows organizations to tailor offerings and messaging more effectively.

In conclusion, the integrated use of predictive modeling and textual analysis provides a comprehensive and actionable view of customer behavior. Whether in the non-profit or commercial context, such a data-driven strategy enables organizations to enhance retention, optimize marketing investments, and ultimately build stronger, longer-lasting relationships with their stakeholders.

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