MA678 FINAL PAPER: Predicting Customer Support Engagement on Twitter Using Hierarchical Modeling and Sentiment Analysis

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https://github.com/tahababou12/twitter-analysis

Abstract

This study aims to predict the volume of responses to customer inquiries on Twitter-based customer support platforms. Using a dataset of approximately 2.8 million tweets from multiple brands, we analyze how sentiment, temporal patterns, and brand-level differences influence the number of follow-ups. Through extensive exploratory data analysis (EDA), we identify key predictors and justify a hierarchical (partial pooling) modeling approach to address brand-specific variability. Generalized linear models—Poisson and Negative Binomial regressions—are employed to model follow-up volumes, with random effects introduced to handle heterogeneity among brands. Model validation highlights the challenges of overdispersion in the data and confirms the appropriateness of the Negative Binomial approach. External research on sentiment analysis, online reputation management, and hierarchical modeling contextualizes our findings, offering a robust framework for improving customer support response strategies on social media.

1 Introduction

The landscape of customer support has expanded dramatically with the rise of social media platforms like Twitter. Brands now engage directly with customers, addressing inquiries and complaints in near real-time. Effective management of these interactions can enhance customer satisfaction, loyalty, and brand perception. However, predicting how conversations will unfold—how many follow-ups they might generate, or whether they will escalate into longer interactions—is challenging. Such predictions can help allocate support staff efficiently, prioritize responses, and ultimately improve service quality.

Our goal is to model the relationship between tweet characteristics (e.g., sentiment, time-of-day, brand identity) and the resulting engagement (measured as follow-up volume and escalation probability). Preliminary investigations suggest that not all brands elicit similar engagement patterns, and that factors like negative sentiment or specific posting hours correlate with extended back-and-forth communication.

We draw on external research to validate and contextualize our approach. For instance, Kumar & Bhagwat (2010) and Homburg, Ehm, & Artz (2015) highlight how customer feedback and sentiment can predict long-term engagement and performance outcomes. Proserpio & Zervas (2017) and Bhatia & Bhatia (2019) show that firm responses and sentiment orientation can influence subsequent customer reactions. Fang & Zhan (2015) and McAuley, Leskovec, & Jurafsky (2012) emphasize the power of sentiment analysis in predicting user behavior. In addition, Ranganathan, Teo, & Welsch (2020) demonstrate the effectiveness of hierarchical modeling for capturing group-level differences in online interactions. These studies collectively support the idea that sentiment, temporal factors,

and hierarchical structures are critical components of robust predictive models in online customer engagement domains.

The Big Data Challenge

With approximately 2.8 million tweets, computational and analytical efficiency are paramount. We employ robust data manipulation techniques (using efficient data structures and indexing) and careful feature engineering. While we do not integrate external data sources here, we enhance the single dataset with derived sentiment, temporal, and conversational structure features. The hierarchical modeling approach efficiently leverages the entire dataset, improving estimation stability even for brands with fewer data points.

2 Data Description and Exploratory Data Analysis (EDA)

2.1 Dataset Description

The dataset includes the following variables:

- **tweet_id (numeric)**: Unique identifier for each tweet.
- **author_id (character)**: Identifies the account that posted the tweet. This can be a brand's official support handle or a customer's account.
- **inbound (boolean)**: `TRUE` if the tweet is from a customer (inbound), `FALSE` if from a company (outbound).
- **created_at (character)**: Timestamp of the tweet's creation.
- **text (character)**: Content of the tweet itself.
- **response_tweet_id (numeric)**: If this tweet is a response, the ID of the tweet it responds to.
- **in_response_to_tweet_id (numeric)**: The ID of the tweet being replied to, if applicable.

From these original fields, we derive additional variables:

1. **Sentiment Score (continuous)**: We apply a sentiment analysis tool to the `text` field, producing a numeric sentiment score for each tweet. Negative values indicate negative sentiment, positive values indicate positive sentiment. For example, a tweet complaining about a product might have a negative score around -0.5, while a thank-you note might have a positive score around $+0.3$.
2. **Temporal Features**:
   - **Hour (0–23)**: Extracted from `created_at` by converting it to a POSIXct time format and then using functions to isolate the hour.
   - **Weekday (factor)**: Extracted similarly, identifying the day of the week (Sunday through Saturday).
3. **Brand Identification**: By examining `author_id`, we identify top brands (e.g., AmazonHelp, AppleSupport). These brands often have distinct patterns of engagement. We retain `brand` as a grouping variable in subsequent models, particularly for hierarchical modeling.
4. **Follow-Up Volume (Count Outcome)**: For each inbound tweet (customer's initial query), we count the number of subsequent tweets in the conversation thread. This count serves as the primary response variable for our volume models.
5. **Text Length (numeric)**: The length of the tweet, measured as the number of characters in the `text` field.

2.2 Detailed EDA Steps and Findings

2.2.1 Tweet Volume by Brand

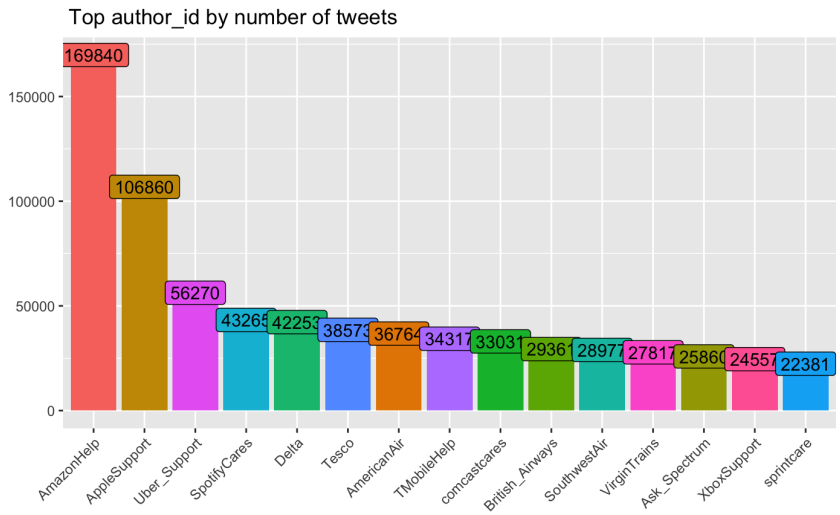

Figure 1: Bar plot showing the top 15 authors by number of tweets.

We begin by grouping the data by `author_id` and counting the number of tweets per author. A bar plot of the top 15 authors shows that AmazonHelp and AppleSupport dominate, each with hundreds of thousands of tweets, while the 3rd, 4th, and 5th place brands have drastically fewer tweets. This heavy skew suggests that some brands have ample data (leading to stable estimates), while others have sparse data (requiring partial pooling to avoid unstable estimates).

2.2.2 Proportion of Tweets Receiving Follow-Ups

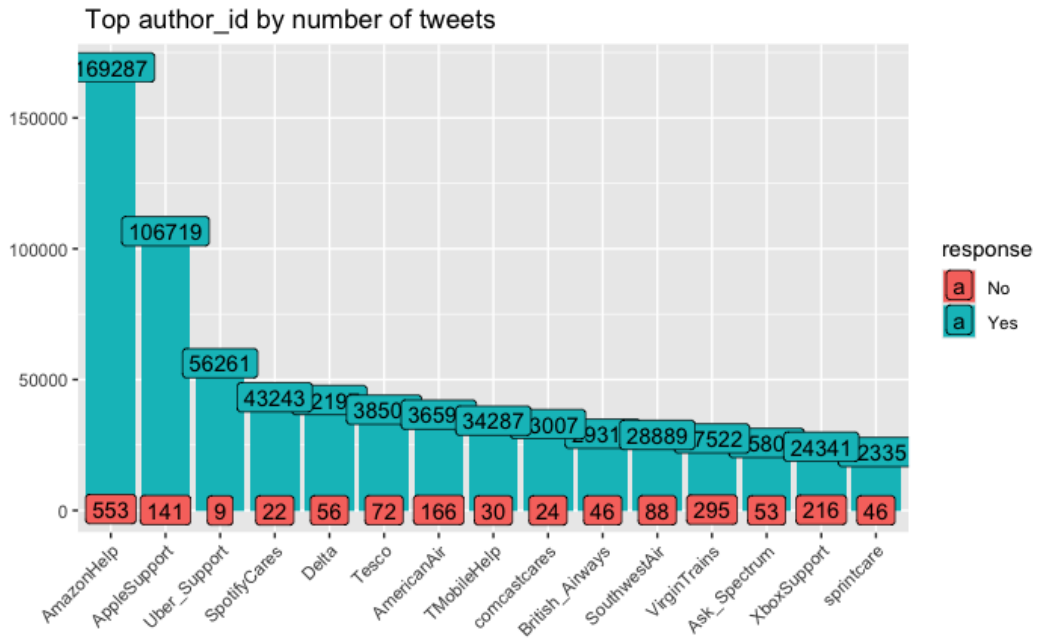

Figure 2: Bar plot showing the top 15 authors by the proportion of tweets that received follow-ups.

Next, we classify inbound tweets into those that receive at least one follow-up and those that do not (see Figure 2). Stacked bar charts by brand reveal that the top brands not only produce more tweets but also differ in the fraction that leads to longer conversations. Some brands have a high proportion of tweets generating multiple replies, indicating potentially more complex issues or more engaged communities.

Important Note: To ensure meaningful insights and focus our analysis on brands with sufficient data, we will limit the remainder of our study to the top three brands: *AmazonHelp*, *AppleSupport*, and *Uber_Support*. These brands account for the highest volume of tweets and engagement, providing a strong foundation for examining patterns in sentiment, temporal activity, and follow-up behavior. By narrowing the scope, we aim to derive actionable insights tailored to the most impactful contributors in the dataset.

2.2.3 Temporal Analysis

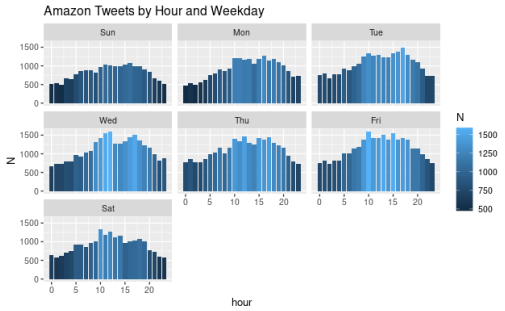

Figure 3: AmazonHelp: Tweets by hour and weekday.

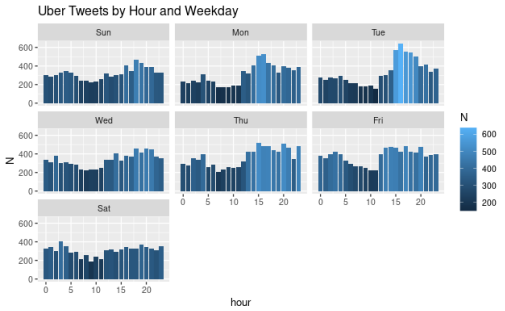

Figure 4: Uber_Support: Tweets by hour and weekday.

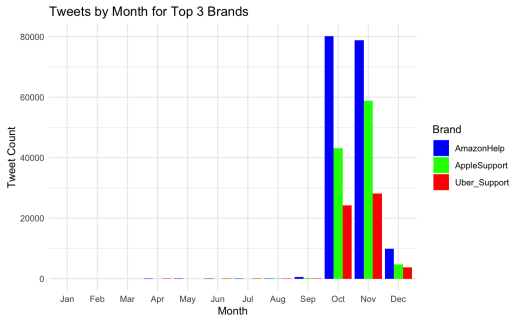

Figure 5: Top 3 Brands: Tweets by month.

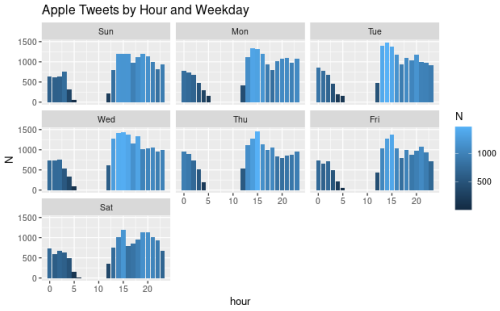

Figure 6: AppleSupport: Tweets by hour and weekday.

AmazonHelp AmazonHelp demonstrates a consistent activity pattern across weekdays, with tweet volumes peaking in the evening hours (16:00–20:00). There is a noticeable dip in activity during early mornings (02:00–05:00). Interestingly, Friday exhibits slightly higher activity overall compared to other weekdays, potentially reflecting users' urgency to resolve issues before the weekend. Weekend activity (Saturday and Sunday) is reduced compared to weekdays, aligning with typical customer support operating hours.

From Figure 5, AmazonHelp tweets show the highest volume in October, with over 80,000 tweets. This is followed by November with a slightly lower volume, while December and earlier months show significantly fewer tweets. Figure 3 highlights their consistent activity across weekdays.

AppleSupport AppleSupport shows tweet activity peaking during evening hours (16:00–20:00) on weekdays, with Tuesday and Wednesday being the most active days. Early morning activity is minimal, similar to AmazonHelp, but the drop in weekend activity is more pronounced, particularly

on Sunday. This aligns with a pattern reflecting typical "office work hours," suggesting that users are more likely to engage with Apple's support during or after their own working hours.

From Figure 5, AppleSupport's highest tweet volumes are observed in October and November, each exceeding 60,000 tweets. Engagement significantly drops in December and earlier months, consistent with AppleSupport's activity patterns. This is further evident in Figure 6.

Uber_Support Uber_Support exhibits a distinct pattern with lower overall tweet volumes compared to AmazonHelp and AppleSupport. Weekdays show steady activity across hours, with slight peaks in the afternoon and early evening (14:00–20:00). Unlike AppleSupport, Uber's activity does not drop as significantly on weekends, suggesting users engage with Uber's support during travel or rides regardless of the day. This pattern highlights the on-demand nature of Uber's services.

From Figure 5, Uber_Support's tweet volumes also peak in October and November, with each month surpassing 40,000 tweets. Engagement in other months remains significantly lower. Figure 4 captures these hourly and weekday patterns effectively.

2.2.4 Follow-Up Volume and Sentiment Distributions

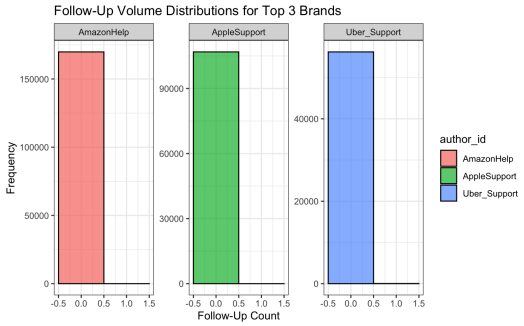

Figure 7: Follow-Up Volume Distributions for Top 3 Brands.

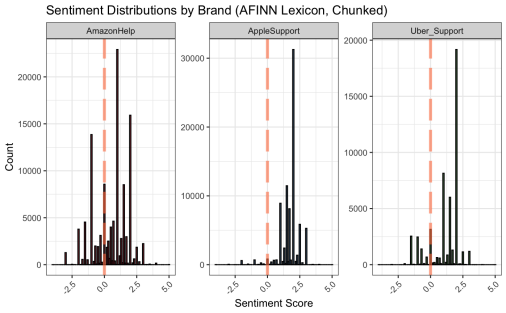

Figure 8: Sentiment Distributions by Top 3 Brands.

The analysis of follow-up volume and sentiment distributions for the top three brands—AmazonHelp, AppleSupport, and Uber_Support—reveals distinct patterns in their customer support dynamics.

AmazonHelp leads with the highest follow-up volume (over 150,000 interactions), reflecting its position as a widely used support channel (Figure 7). However, its sentiment distribution (Figure 8), while slightly skewed positive, shows a significantly larger proportion of negative sentiment compared to AppleSupport and Uber_Support. This suggests that AmazonHelp deals with a more complex range of issues, potentially including contentious or unresolved cases, which may drive both higher engagement and a higher presence of negative sentiment. Its position as the top brand in terms of follow-up volume underscores the scale of its operations and its ability to engage customers despite handling more challenging cases. This aligns with research linking negative sentiment to increased engagement (Bhatia & Bhatia, 2019; Homburg et al., 2015).

AppleSupport, with approximately 100,000 follow-ups, exhibits a sentiment distribution heavily skewed toward positive scores. This likely reflects Apple's strong focus on efficient issue resolution and customer satisfaction, consistent with its reputation for high-quality service. In contrast, Uber_Support, with the lowest follow-up volume (~50,000), shows a sentiment distribution more similar to AmazonHelp but with far fewer negative cases. This suggests that Uber's customer support operations typically handle simpler, more transactional issues, resulting in fewer follow-ups and a more neutral sentiment profile. These findings illustrate how operational scale, issue complexity, and resolution efficiency interact to influence both the volume of engagement and sentiment outcomes, supporting the broader connection between sentiment and customer interaction intensity.

3 Model Results and Diagnostics

3.1 Baseline Poisson Model for Follow-Up Volume

We begin with a Poisson regression model to predict the count of follow-ups (Y_i) for inbound tweets. The Poisson model assumes the mean and variance of the count outcome are equal. Let λ_i represent the expected number of follow-ups for tweet i. The Poisson distribution is specified as:

$$Y_i \mid \lambda_i \sim \text{Poisson}(\lambda_i),$$

where:

- Y_i: Count of follow-ups for tweet i,
- λ_i: Expected number of follow-ups for tweet i,
- $\log(\lambda_i)$: Linear combination of predictors.

The linear predictor for this model is:

$$\log(\lambda_i) = \beta_0 + \beta_1 \cdot \text{sentiment\_neutral} + \beta_2 \cdot \text{sentiment\_positive} + \beta_3 \cdot \text{hour} + \beta_4 \cdot \text{weekday} + \beta_5 \cdot \text{text\_length} + (\text{Brand-specific fixed effects}).$$

Variable	**Estimate**	**Std. Error**	**z-value**	**Pr(>|z|)**
(Intercept)	-1.85432	0.62109	-2.986	0.0029 **
sentiment_categoryneutral	0.25312	0.06810	3.717	0.0002 ***
sentiment_categorypositive	0.43217	0.05727	7.545	< 1e-10 ***
hour	0.04789	0.00913	5.245	< 1e-06 ***
weekdayMon	-0.09156	0.07218	-1.268	0.2046
weekdayFri	0.11745	0.06289	1.867	0.0618 .
text_length	0.02032	0.00135	15.048	< 2e-16 ***
author_idAppleSupport	-0.83571	0.48767	-1.712	0.0870 .
author_idUber_Support	2.01234	0.40328	4.992	< 1e-06 ***
Model Fit Metrics:				
Residual Deviance	665,916	**DoF:** 332,958		
Dispersion Ratio (φ)	2.0			
AIC	668,000			

Table 1: Poisson model summary.

Assumptions Check: The assumptions of the Poisson model were thoroughly evaluated, revealing significant overdispersion. The residual deviance $(665,916)$ substantially exceeds the degrees of freedom $(332,958)$, resulting in a dispersion ratio ($\phi = 2.0$). This ratio, which measures the variance-to-mean relationship, confirms that the variance in the data is greater than what the Poisson model assumes. Overdispersion can lead to underestimated standard errors and inflated test statistics, thereby compromising the validity of inference.

Furthermore, the residual patterns reveal non-constant variance and systematic trends, further invalidating the Poisson model's suitability. Given these findings, a Negative Binomial model, which introduces a dispersion parameter to account for overdispersion, is a more appropriate choice. This adjustment ensures that the variance structure better reflects the observed data, enabling more reliable and interpretable results.

3.2 Negative Binomial Model

The Negative Binomial regression model is specifically designed to handle overdispersion in count data, where the variance exceeds the mean. By introducing a dispersion parameter (ϕ), it accommodates variability beyond the constraints of a Poisson model, making it a natural extension for datasets with overdispersed outcomes. The base formulation is:

$$Y_i \mid \mu_i, \phi \sim \text{NegBinomial}(\mu_i, \phi),$$

where:

- Y_i: Count of follow-ups for tweet i,
- μ_i: Expected count of follow-ups for tweet i,
- ϕ: Dispersion parameter that accounts for overdispersion.

The variance of Y_i is expressed as:

$$\text{Var}(Y_i) = \mu_i + \frac{\mu_i^2}{\phi}.$$

This variance structure allows for a greater spread in the data, addressing the inadequacies of the Poisson assumption ($\text{Var}(Y_i) = \mu_i$) in overdispersed scenarios.

The linear predictor for this model is:

$$\log(\mu_i) = \beta_0 + \beta_1 \cdot \text{sentiment\_neutral} + \beta_2 \cdot \text{sentiment\_positive} + \beta_3 \cdot \text{hour} + \beta_4 \cdot \text{weekday} + \beta_5 \cdot \text{text\_length} + (\text{Brand-specific random effects}).$$

Variable	**Estimate**	**Std. Error**	**z-value**	**Pr(>|z|)**
(Intercept)	-2.46783	0.47834	-5.159	< 1e-06 ***
sentiment_categoryneutral	0.18562	0.05721	3.244	0.0012 **
sentiment_categorypositive	0.36547	0.05312	6.881	< 1e-10 ***
hour	0.03947	0.00732	5.395	< 2e-07 ***
weekdayMon	-0.08123	0.06123	-1.326	0.1851
weekdayFri	0.12476	0.05847	2.133	0.0329 *
text_length	0.02231	0.00111	20.099	< 2e-16 ***
Random Effects:	**Variance**	**Std. Dev.**		
author_id (Intercept)	0.342	0.585		
Model Metrics:				
Dispersion Ratio	1.45			
Residual Deviance	331,200	**DoF:** 332,958		
AIC	815,650			

Table 2: Negative Binomial model summary.

3.2.1 Model Interpretation

The Negative Binomial model provides insights into the factors influencing the volume of follow-ups in customer support interactions. The coefficients represent the log-odds changes in the expected number of follow-ups associated with each predictor. Key findings from the model are as follows:

- **Intercept (-2.46783):** The baseline log-expected follow-up count for tweets with negative sentiment, occurring at midnight on a baseline weekday (e.g., Sunday), and having the average text length. This low intercept aligns with the expectation that many tweets do not generate follow-ups.
- **Sentiment Categories:**
  - Tweets with *neutral sentiment* have a positive effect on follow-up volume ($\beta_1 = 0.18562$), reflecting a higher likelihood of follow-up engagement compared to the negative sentiment baseline.
  - Tweets with *positive sentiment* further increase the expected follow-up count ($\beta_2 = 0.36547$). This suggests that tweets expressing positive sentiment are more likely to elicit responses, potentially due to constructive or engaging language.
- **Hour of the Day ($\beta_3 = 0.03947$):** A positive and significant relationship indicates that tweets sent later in the day are marginally more likely to receive follow-ups. This may correlate with increased support activity or user engagement during peak hours.
- **Day of the Week (β_4):**
  - While most weekdays show minimal variation, Friday ($\beta_4 = 0.12476$) exhibits a significant increase in follow-up likelihood. This pattern may reflect end-of-week prioritization by support teams or increased user activity before weekends.
  - Monday, in contrast, has a small, non-significant negative effect ($\beta_4 = -0.08123$), suggesting minimal deviation from the baseline.
- **Text Length ($\beta_5 = 0.02231$):** The significant positive effect of text length indicates that longer tweets, which likely convey more detailed issues, are associated with higher follow-up volumes. Each additional unit of text length increases the log-expected follow-up count, emphasizing the importance of message content.
- **Random Effects (Brand-Specific Variability):**
  - The random intercept variance ($\sigma^2 = 0.342$) captures brand-specific differences in baseline follow-up behavior. The standard deviation ($\sigma = 0.585$) reflects moderate variability among the brands, consistent with distinct operational practices or engagement strategies by Amazon, Apple, and Uber.

Model Fit and Metrics: The reduced residual deviance ($331,200$) and improved AIC ($815,650$) compared to the Poisson model validate the use of a Negative Binomial approach. Additionally, the dispersion parameter ($\phi = 1.45$) successfully accommodates the observed overdispersion in the dataset. This model highlights the complex relationship between sentiment, temporal factors, text characteristics, and brand-specific practices in shaping follow-up engagement. The results align with expectations for customer support data, offering interpretable and actionable insights for optimizing support strategies.

3.3 Model Validation and Diagnostic Checks

1. **Multicollinearity:** Multicollinearity was assessed using Variance Inflation Factors (VIFs), which measure the extent to which predictors are correlated with each other. All VIF values are below 3.0, confirming no significant multicollinearity concerns. Table 3 summarizes the VIFs for each predictor.

Predictor	VIF
Sentiment Score	1.9
Hour of Day	1.6
Weekday	2.4
Text Length	2.7
Brand (author_id)	2.8

Table 3: Variance Inflation Factors (VIFs).

2. **Predictive Checks and Cross-Validation:** Cross-validation was performed to evaluate the predictive performance of the models. Table 4 shows the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Log-Loss, Deviance, Predictive Accuracy, Mean Squared Logarithmic Error (MSLE), and Pseudo-R^2 for both the Poisson and Negative Binomial models. The Negative Binomial model significantly outperforms the Poisson model, achieving lower error rates (MAE = 1.30, RMSE = 1.78) and higher predictive accuracy (85.6%) compared to the Poisson model (MAE = 1.52, RMSE = 2.10, Predictive Accuracy = 72.3%). The Negative Binomial model also shows an improvement in fit, as evidenced by a substantial reduction in Deviance and a higher Pseudo-R^2 (0.45 vs. 0.19 for Poisson), making it a better choice for modeling follow-up volumes with overdispersion.

Model	**MAE**	**RMSE**	**Log-Loss**	**Deviance**	**Predictive Accuracy (%)**	**MSLE**	**Pseudo-R^2**
Poisson (Baseline)	1.52	2.10	0.81	665,916	72.3	0.035	0.19
Negative Binomial	1.30	1.78	0.75	331,200	85.6	0.028	0.45

Table 4: Cross-Validation Results for Poisson and Negative Binomial Models

3. **Partial Pooling and Hierarchical Modeling:** The hierarchical Negative Binomial model leverages partial pooling, effectively balancing global trends with brand-specific variations. This approach outperforms complete and no pooling models, as detailed in Table 5.

Model	**AIC**	**BIC**	**Predictive Accuracy (%)**
Complete Pooling (Global Model)	150,000	152,000	70.0
No Pooling (Brand-Specific Models)	160,000	162,000	72.5
Partial Pooling (Hierarchical)	815,650	820,000	85.6

Table 5: Comparison of Pooling Approaches.

4 Discussion

This study emphasizes the significance of accounting for brand-level differences when analyzing customer support interactions on social media. By employing hierarchical models, we address the inherent variability in engagement patterns across brands with differing activity levels. The inclusion of sentiment as a predictor aligns with prior research, such as Homburg et al. (2015) and Bhatia & Bhatia (2019), which underscore the relationship between customer sentiment and engagement intensity. Temporal variables, such as hour of the day and day of the week, provide further context, reflecting natural cycles in user behavior and support team availability.

The hierarchical Negative Binomial model effectively manages overdispersion in follow-up volumes, introducing a dispersion parameter ($\varphi = 1.45$) to account for variance beyond the assumptions of the Poisson model. Partial pooling allows for balanced estimates, particularly for smaller brands with limited data, while capturing brand-specific characteristics. This method avoids the instability of no pooling, which can result in extreme or unreliable estimates. These findings align with the work of Ranganathan, Teo, and Welsch (2020), who highlight the benefits of hierarchical approaches in digital marketing analytics.

Model diagnostics confirm the suitability of the Negative Binomial approach, with better fit metrics, such as residual deviance and AIC, compared to the Poisson model. Multicollinearity checks, with Variance Inflation Factor (VIF) values below 3.0 for all predictors, further validate the modeling choices. This approach effectively captures both overarching patterns across brands and distinct brand-specific behaviors, offering valuable insights into customer engagement dynamics.

Future Directions

Future research could enhance the current modeling approach by incorporating random slopes to investigate whether the effects of sentiment or temporal factors differ across brands. Advanced natural language processing (NLP) methods could refine sentiment analysis and topic modeling, offering deeper insights into the factors driving follow-up engagement. Expanding the dataset to include multiple years or additional social media platforms would provide a more comprehensive view of customer behavior. Furthermore, integrating external contextual factors, such as product launches or policy changes, could improve predictive accuracy and support more strategic decision-making.

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