SIMON FRASER UNIVERSITY

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COMPUTATIONAL DATA SCIENCE

# Analyzing the Impact of Posting Time on Instagram Reels Engagement

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# 1 Introduction

## 1.1 Problem Statement

Social media platforms like Instagram are becoming essential for realtors in the Lower Mainland to reach clients and showcase their business. Instagram Reels, a short-form video content, offer a visually appealing way to engage audiences, increasing visibility, brand recognition, and business growth. However, it remains unclear if posting times can significantly affect engagement levels. This analysis investigates whether the day and time of posting impact Instagram Reel engagement for realtors. By identifying engagement patterns, we aim to provide actionable insights to enhance cost-effective social media strategies and boost audience interaction.

# 2 Data Description

## 2.1 Data Collection

The dataset for this analysis was derived from a previous project involving the collection of Instagram data for 2,753 real estate agents in the Lower Mainland. The data was collected on July 31, 2024, within 24 hours, using an automated Python system with Selenium. The scraper captured publicly available Instagram data, employing proxies and web automation to parse JSON responses into CSV format. To ensure anonymity, all PII such as usernames and emails was removed, and users were assigned arbitrary IDs. Unfortunately, due to an NDA, the scraper program cannot be included in the project repository.

## 2.2 Data Overview

### 2.2.1 Account-Level Data

The dataset includes an anonymized user ID, scrape status and timestamp (UTC), account type (e.g., verified, business), and counts of followers, followings, and total posts.

### 2.2.2 Content-Level Data

The dataset captures up to 36 of the most recent Reels per account, including upload timestamp (UTC), views, likes, comments, duration (seconds), audio presence, and comment section status (disabled or not). Data for other post types, such as images or carousels, was disregarded, as the focus is on Instagram Reels.

# 3 Methodology

## 3.1 Data Cleaning and Preprocessing

### 3.1.1 Filtering Accounts

Accounts that failed scraping, lacked Reels, were private were excluded. Furthermore, accounts with fewer than 12 posts or 50 followers were removed to focus the analysis on active realtors with a meaningful presence on Instagram. The filters reduced the dataset from 2,753 to 2,095 accounts.

### 3.1.2 Excluding Influencer Accounts

Influencers are high-profile users that could disproportionately skew the analysis, as they often have significantly higher engagement metrics that do not reflect the norm for realtors. To maintain a level of homogeneity in the data, accounts above the 98th percentile in follower counts were removed, leaving 2,053 accounts. This allowed for more generalizable insights applicable to the majority of realtors.

### 3.1.3 Transforming to Reel-Based Data

The account-level data was melted and pivoted into a Reel-based format, resulting in 36 * 2,053 = 73,908 records, each representing a single Reel with associated metrics and author information.

### 3.1.4 Time Conversion

Scraping and posting timestamps were converted from UTC to PST to accurately reflect the time in the Lower Mainland.

### 3.1.5 Filtering Reels

Since not all accounts had as many as 36 Reels, many of the records were empty. Such records were identified by missing posting timestamps and were excluded. Additionally, Reels with disabled comment sections or abnormal durations (less than 1 second or more than 90 seconds) were removed. Videos exceeding Instagram's 90-second limit or extremely short videos were considered non-standard. These filters reduced the dataset to 39,262 Reels.

### 3.1.6 Handling Recent Reels

A crucial assumption was that, as new social media content tends to have high visibility only for a short period after posting, engagement typically stabilizes after the short period, with negligible additional likes, comments, or views. By checking the distribution of time elapsed since posting (Figure 1), we found the cutoff of 7-day fits our conjecture. Removing Reels posted within 7 days of the scrape date resulted in reasonably minimal data loss (2.8%), reducing the size of dataset to 38,166 Reels.

### 3.1.7 Categorizing Posting Times

Reels were categorized based on the day of the week and time of day they were posted. Days was numbered from 1 (Monday) to 7 (Sunday). The distribution (Figure 2) was reasonably balanced. Time was initially divided into four bins: **Morning** (05:00-11:59), **Afternoon** (12:00-16:59), **Evening** (17:00-23:59), and **Night** (00:00-04:59). However, due to the low percentage (2.3%) of Reels posted at Night (Figure 3), this category was merged into Evening, resulting in three final bins: **Morning** (05:00-11:59), **Afternoon** (12:00-16:59), and **Evening** (17:00-04:59). This adjustment produced balanced and interpretable groups (Figure 4) and aimed to maintain meaningful distinctions relevant to user engagement patterns, particularly reflecting times outside typical business hours.

### 3.1.8 Handling Missing Values

The only feature with missing values after filtering was the view counts of Reels, with 5,974 missing out of 38,166 Reels (15.65%). Simply discarding these Reels or naively imputing average values could severely compromise data integrity.

To determine if the missing values were meaningful (e.g., were they equivalent to the real zero-view?), we conducted preliminary analysis and found no significant differences between Reels with and without view counts in terms of likes, comments, or durations. However, Figure 5 showed a clear pattern: the likelihood of missing views increased with the age of the Reel, reaching 37.6% at 1,000 days and nearly 100% at 2,250 days. This suggested that the missingness was likely due to external factors such as archiving or limitations in data availability, and that an imputation would be reasonable.

We decided to use Random Forest (RF) imputation, leveraging predictors such as likes, followers, and time elapsed. RF's ability to model non-linear relationships made it suitable for addressing the systematic missingness we observed above. To avoid multicollinearity (Figure 6), comments count, which was highly correlated with likes (corr=0.73), was excluded from the feature set, while other mild correlations showed minimal impact on predictability. The feature set allowed the model to infer relationships that might compensate for the systematic absence of views in older Reels.

The target variable was the log-transformed view counts, which showed approximately normal distribution. The fitted model achieved a good accuracy (R-squared) of 0.81. The residual analysis (Figure 7) showed no obvious violations, confirming the model's validity. The predicted views were exponentiated back to fill the missing cells. This method preserved the dataset's size and integrity, minimizing bias and enabling comprehensive analysis.

### 3.1.9 Outlier Detection and Removal

The dataset contained substantial outliers, such as Reels with unusually high likes or comments relative to views or the author's follower count. In addition, some high-performing Reels went so viral that they became unrepresentative and disproportionately skewed the analysis. To address the extremes in engagement metrics, outliers were identified and removed using two methods. First, we employed a DBSCAN Clustering algorithm that statistically detected 19 outliers (Table 1) based on standardized features (followers, likes, comments, and views).

Detecting only 19 outliers out of 38,166 Reels suggested us to apply additional methods: Sequential Filtering. Reels with views above the 98th percentile were first removed. Since Reels with extreme views usually have extreme likes or comments, to prevent over-filtering and retained authentic high-performing Reels, we further removed Reels with likes above the 99th percentile, and then those with comments above the 99th percentile.

The final Reel dataset consisted of approximately 36,631 Reels more representative of typical Reels, with engagement metrics exhibiting more normalized distributions.

#### 3.1.10 Independence of Observations

A challenge in this analysis is that multiple Reels from the same user are unlikely to be fully independent, as consistent styles and content quality across a user's account can influence engagement metrics.

To address this, we normalized engagement metrics (detailed in the next section) to account for differences in audience size, assuming qualitative traits are reflected in quantitative metrics (i.e., higher quality drives better engagement). Additionally, multiple Reels from the same user within the same time slot were averaged into a single observation, reducing the dataset to 20,565 Reels. This step mitigates the risk of a user's activity inflating the perceived impact of certain posting times, though user-specific influence across bins remains.

While these measures reduce user-level dependencies, they do not eliminate them. We acknowledge residual correlation and accept its potential influence on the analysis, allowing us to proceed with caution.

### 3.2 Engagement Metrics

To normalize engagement across users with varying follower base, the **Engagement Per Follower (EPF)** metric was introduced for each aggregated observation using the formula:

$$EPF = \frac{\text{Likes Count} + \text{Comments Count}}{\text{Followers Count}} \times 1000$$

This metric represents the number of likes and comments per 1,000 followers, with the scaling factor improving distribution suitability for analysis. Due to significant right skewness, the EPF was log-transformed:

$$log\_EPF = \log\left(\left(\frac{\text{Likes Count} + \text{Comments Count}}{\text{Followers Count}} + 1\right) \times 1000\right)$$

The transformation produced an approximately normal distribution (Figure 8), with a slight left-tail deviation near zero, where many Reels had no engagement.

### 3.3 Statistical Analysis Techniques

To determine whether mean EPF differed across day-time groups, we employed a one-way Analysis of Variance (ANOVA), which efficiently tests multiple groups simultaneously while controlling the Type I error rate.

#### 3.3.1 Test Assumptions

- **Independence**: Data aggregation and normalization minimized dependence, though complete independence is not guaranteed due to multiple Reels across day-time groups per user.

- **Equal-Variances**: Levene's test confirmed the homogeneity of variances across groups (p-value = $0.41 > 0.05$), satisfying this assumption.

- **Normality**: Tests of normality found deviations from the normal distribution assumption (p-value = $2.565 \times 10^{-77} < 0.05$). However, the large sample size ($n = 20,565$) and relatively balanced group sizes allow the Central Limit Theorem (CLT) to mitigate this violation.

By ensuring these assumptions were reasonably addressed, ANOVA was applied to examine differences in EPF across day-time groups.

# 4 Results and Findings

## 4.1 Descriptive Statistics

Figure 9 presents the mean EPF for each day-time category, highlighting higher engagement during evenings and the weekend, and lower values during mornings and early weekdays. Figure 10 illustrates fluctuating engagement patterns on a sequential timeline, suggesting posting time may influence Reel performance and justifying the employment of statistical tests.

## 4.2 ANOVA Results

The ANOVA revealed a statistically significant difference in mean EPF across day-time groups (p-value = $4.795 \times 10^{-18} < 0.05$), confirming that posting day and time impact engagement. Residual analysis (Figure 11) showed the model fit the data well. The histogram of residuals approximated normality, and while the Q-Q plot showed slight deviations in the tails, most points aligned closely with the diagonal. The Residuals vs. Fitted Values plot indicated no systematic bias, with residuals centered around 0 and relatively constant variance.

## 4.3 Post-Hoc Analysis with Tukey HSD

Tukey's HSD test identified 39 significant pairwise differences (Table 2). Evenings on weekends consistently outperformed early-week mornings, emphasizing that posting time significantly influences engagement. In some cases, the differences in mean EPF were large enough to demonstrate strong statistical significance.

# 5 Discussion

## 5.1 Interpretation of Findings

The findings confirm that posting time significantly impacts Reel engagement. Evening slots, especially late-week, show higher EPF, while early-week mornings exhibit lower engagement. These trends align with common assumptions about increased social media activity during off-peak work hours and weekends.

Normalization and aggregation during preprocessing reduced the influence of outliers and user-specific biases. While these steps cannot fully eliminate extremes and dependencies, the significant differences suggest that temporal factors play a meaningful role in engagement outcomes.

## 5.2 Practical Recommendations

Realtors can use these insights to optimize posting schedules. Focusing on high-engagement periods, such as weekend evenings, can increase audience engagement and interaction. While content quality remains critical, aligning posting times with peak engagement can enhance visibility and serve as a data-driven strategy for improving social media performance.

# 6 Assumptions and Limitations

Several assumptions and limitations must be acknowledged when interpreting these results.

## 6.1 Data and Content-Related Assumptions

### 6.1.1 Homogeneity of Content Themes

We assumed that Reels from different users could be meaningfully compared after normalization by follower counts. However, qualitative differences in content quality, themes, and visual appeal will likely introduce user-specific correlations. While normalization and aggregation mitigate some dependencies, the lack of data on content style means that the independence assumptions of the test are only partially addressed.

### 6.1.2 Handling Influencer Accounts

Outliers were bluntly removed by excluding accounts above the 98th percentile in follower counts. This approach risks excluding successful local realtors while retaining borderline cases that may still skew results. A more nuanced criterion, incorporating engagement ratios or additional metadata, could better distinguish true influencers from representative accounts.

#### 6.1.3 Temporal Assumptions on Engagement Accumulation

We assumed that Reels accumulate negligible engagement after seven days, leading us to exclude recently posted Reels. This decision was guided by observed engagement patterns and practical considerations but was not formally validated with engagement data. In future work, more robust methods could justify or refine this cutoff.

#### 6.1.4 Time Binning Without Formal Proof

The three time bins (Morning, Afternoon, Evening) were chosen for balance between interpretability and data distribution. However, these ranges lack formal validation and may not fully capture user behavior patterns. Alternative binning strategies or continuous time modeling could offer more nuanced insights.

### 6.2 Data Transformations and Outlier Management

#### 6.2.1 Imputation of Missing Views Using Random Forest

The Random Forest imputation assumes two key conditions: (1) patterns observed in recent Reels apply to older Reels, presuming temporal consistency in relationships between predictors (e.g., likes) and view counts; and (2) missingness associated with older Reels does not introduce significant unmeasured biases. While reasonable given the lack of major differences observed between Reels with and without view counts, these assumptions remain prone to errors. Shifts in user behavior or platform features over time could cause systematic misrepresentation of historical engagement levels. Additionally, if missing views reflect factors beyond our predictors, genuine temporal trends might be distorted.

#### 6.2.2 Outlier Detection and Filtering

Outliers were removed using DBSCAN clustering (19 outliers) and percentile cutoffs (98th for views, 99th for likes and comments). While this improved distributional shapes, the thresholds were arbitrarily given via manual review and lacked formal evaluation. More rigorous or domain-informed methods could yield a cleaner dataset.

#### 6.2.3 Choice of Engagement Metric (EPF)

The EPF metric, based on likes, comments, and follower counts, simplified comparisons but excluded views and other potential engagement metrics. Despite significant effort spent imputing missing views, these values were ultimately unused in the analysis, limiting the metric's ability to fully capture content performance. Developing a more comprehensive scoring model that incorporates views could enhance future analyses.

### 6.3 Dependency and Non-Normality

User-level correlations persist despite normalization and aggregation, and observations cannot be considered fully independent. While ANOVA's robustness to normality violations given a large data size allows meaningful analysis, non-normal residuals and correlated observations suggest caution. These limitations highlight the need for more sophisticated models (e.g., Mixed Effect Models) to address the complexity of social media data.

## 7 Conclusion

The analysis confirms that the timing of Instagram Reel postings matters for engagement. Despite certain assumptions and limitations, the results strongly indicate that evening slots, particularly near the end of the week, consistently yield higher engagement levels, while mornings early in the week are less effective. These findings highlight the importance of scheduling strategies in maximizing audience interaction. To enhance engagement, realtors should focus on posting Reels during the identified high-engagement periods while regularly reviewing audience response and adjusting schedules accordingly.

# A Appendix

## A.1 Project Experience Summary

- (Shared) Engineered a full data analytics cycle in Python using pandas, NumPy, and scikit-learn, uncovering temporal audience engagement patterns by performing data cleaning, data transformation, metric design, and model fitting on 2,700 accounts and 40,000 Instagram Reels.
- (Mirrien) Enhanced data quality and completeness by implementing Random Forest imputation for non-random missing data and DBSCAN-based outlier detection, retaining 95% of records and ensuring stable distributions for reliable statistical testing.
- (Ohm) Provided quantifiable performance benchmarks by applying ANOVA and Tukey HSD, uncovering 39 significant temporal differences and quantifying a 20% average increase in engagement during weekend evenings compared to early-week mornings.
- (Shared) Employed Matplotlib and seaborn to create 10+ data-driven visualizations that translated raw engagement metrics into clear, actionable insights, supporting strategic posting schedules to boost audience interaction.
- (Shared) Leveraged Git for version control and iterative improvements and delivered findings in LaTeX, increasing reproducibility, clarity, and stakeholder confidence in the actionable insights.

## A.2 Tables

Table 1: Outliers Identified by DBSCAN

| Followers | Likes Count | Comments Count | Video View Count |
|---|---|---|---|
| 5905 | 5833 | 15790 | 58410 |
| 6766 | 983 | 175 | 9818 |
| 10048 | 2214 | 148 | 4538 |
| 28131 | 6856 | 20841 | 182141 |
| 28705 | 414 | 226 | 7975 |
| 30046 | 1571 | 5264 | 718445 |
| 30781 | 1723 | 3 | 11958 |
| 31821 | 1504 | 16003 | 403498 |
| 35246 | 1156 | 336276 | 13618871 |
| 35276 | 1156 | 78829 | 2084066 |
| 36914 | 3600 | 15738 | 65838 |
| 40755 | 15240 | 112518 | 4652029 |
| 45980 | 5878 | 3 | 5463 |
| 45995 | 5878 | 185 | 2345 |
| 53999 | 1628 | 308 | 14297 |
| 54152 | 11989 | 67570 | 1069829 |
| 63432 | 4640 | 14661 | 293542 |
| 70060 | 1989 | 49503 | 816261 |
| 70078 | 1989 | 63132 | 829023 |

Table 2: Significant Pairwise Comparisons by Tukey HSD

| Group 1 | Group 2 | Mean Diff | p-adj | Lower | Upper | Reject |
|---|---|---|---|---|---|---|
| 1_Morning | 7_Evening | 0.3054 | 0.0000 | 0.1206 | 0.4902 | True |
| 1_Morning | 6_Evening | 0.2918 | 0.0000 | 0.1102 | 0.4735 | True |
| 3_Morning | 7_Evening | 0.2824 | 0.0000 | 0.1010 | 0.4639 | True |
| 4_Morning | 7_Evening | 0.2735 | 0.0000 | 0.0934 | 0.4536 | True |
| 3_Morning | 6_Evening | 0.2689 | 0.0000 | 0.0907 | 0.4471 | True |
| 2_Morning | 7_Evening | 0.2672 | 0.0000 | 0.0846 | 0.4498 | True |
| 4_Morning | 6_Evening | 0.2599 | 0.0000 | 0.0830 | 0.4369 | True |
| 2_Morning | 6_Evening | 0.2536 | 0.0001 | 0.0742 | 0.4331 | True |
| 1_Morning | 3_Evening | 0.2522 | 0.0000 | 0.0849 | 0.4195 | True |
| 4_Afternoon | 7_Evening | 0.2370 | 0.0004 | 0.0588 | 0.4153 | True |
| 1_Afternoon | 7_Evening | 0.2339 | 0.0008 | 0.0529 | 0.4148 | True |
| 4_Afternoon | 6_Evening | 0.2234 | 0.0010 | 0.0484 | 0.3985 | True |
| 1_Afternoon | 6_Evening | 0.2203 | 0.0018 | 0.0425 | 0.3981 | True |
| 2_Morning | 3_Evening | 0.2140 | 0.0007 | 0.0491 | 0.3789 | True |
| 2_Afternoon | 7_Evening | 0.2135 | 0.0042 | 0.0333 | 0.3937 | True |
| 1_Morning | 5_Evening | 0.2123 | 0.0016 | 0.0422 | 0.3825 | True |
| 1_Morning | 7_Afternoon | 0.2007 | 0.0066 | 0.0268 | 0.3745 | True |
| 2_Afternoon | 6_Evening | 0.2000 | 0.0093 | 0.0230 | 0.3770 | True |
| 3_Afternoon | 7_Evening | 0.1996 | 0.0100 | 0.0221 | 0.3770 | True |
| 5_Morning | 7_Evening | 0.1961 | 0.0183 | 0.0146 | 0.3775 | True |
| 1_Morning | 2_Evening | 0.1947 | 0.0064 | 0.0264 | 0.3629 | True |
| 3_Morning | 5_Evening | 0.1894 | 0.0084 | 0.0229 | 0.3559 | True |
| 3_Afternoon | 6_Evening | 0.1860 | 0.0216 | 0.0118 | 0.3602 | True |
| 5_Afternoon | 7_Evening | 0.1850 | 0.0323 | 0.0065 | 0.3636 | True |
| 5_Morning | 6_Evening | 0.1825 | 0.0376 | 0.0043 | 0.3607 | True |
| 1_Afternoon | 3_Evening | 0.1806 | 0.0127 | 0.0176 | 0.3437 | True |
| 4_Morning | 5_Evening | 0.1804 | 0.0155 | 0.0153 | 0.3456 | True |
| 1_Morning | 6_Afternoon | 0.1787 | 0.0172 | 0.0140 | 0.3433 | True |
| 3_Morning | 7_Afternoon | 0.1777 | 0.0294 | 0.0075 | 0.3480 | True |
| 1_Morning | 4_Evening | 0.1764 | 0.0230 | 0.0104 | 0.3423 | True |
| 2_Morning | 5_Evening | 0.1741 | 0.0317 | 0.0063 | 0.3420 | True |
| 2_Evening | 3_Morning | -0.1717 | 0.0295 | -0.3363 | -0.0072 | True |
| 1_Evening | 2_Morning | -0.1760 | 0.0243 | -0.3422 | -0.0097 | True |
| 1_Evening | 4_Morning | -0.1823 | 0.0115 | -0.3458 | -0.0188 | True |
| 3_Evening | 4_Afternoon | -0.1838 | 0.0072 | -0.3438 | -0.0237 | True |
| 1_Evening | 3_Morning | -0.1912 | 0.0061 | -0.3561 | -0.0263 | True |
| 1_Evening | 1_Morning | -0.2142 | 0.0011 | -0.3828 | -0.0456 | True |
| 3_Evening | 4_Morning | -0.2203 | 0.0002 | -0.3824 | -0.0581 | True |
| 3_Evening | 3_Morning | -0.2292 | 0.0001 | -0.3928 | -0.0657 | True |

### A.3 Figures

Figure 1: The Distribution of Reels based on the Time Elapsed

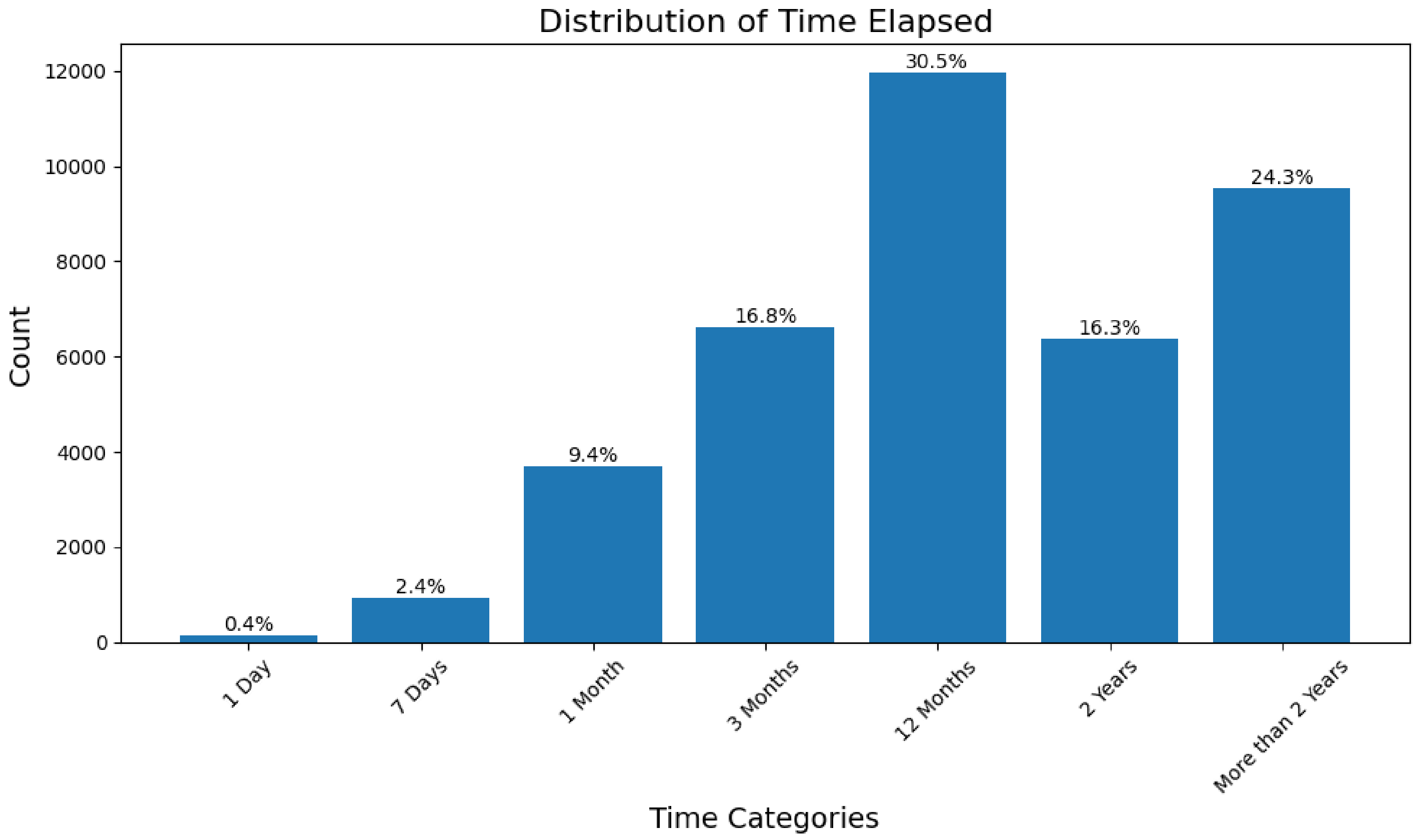

Figure 2: The Distribution of Reels based on the Day of Week in PST

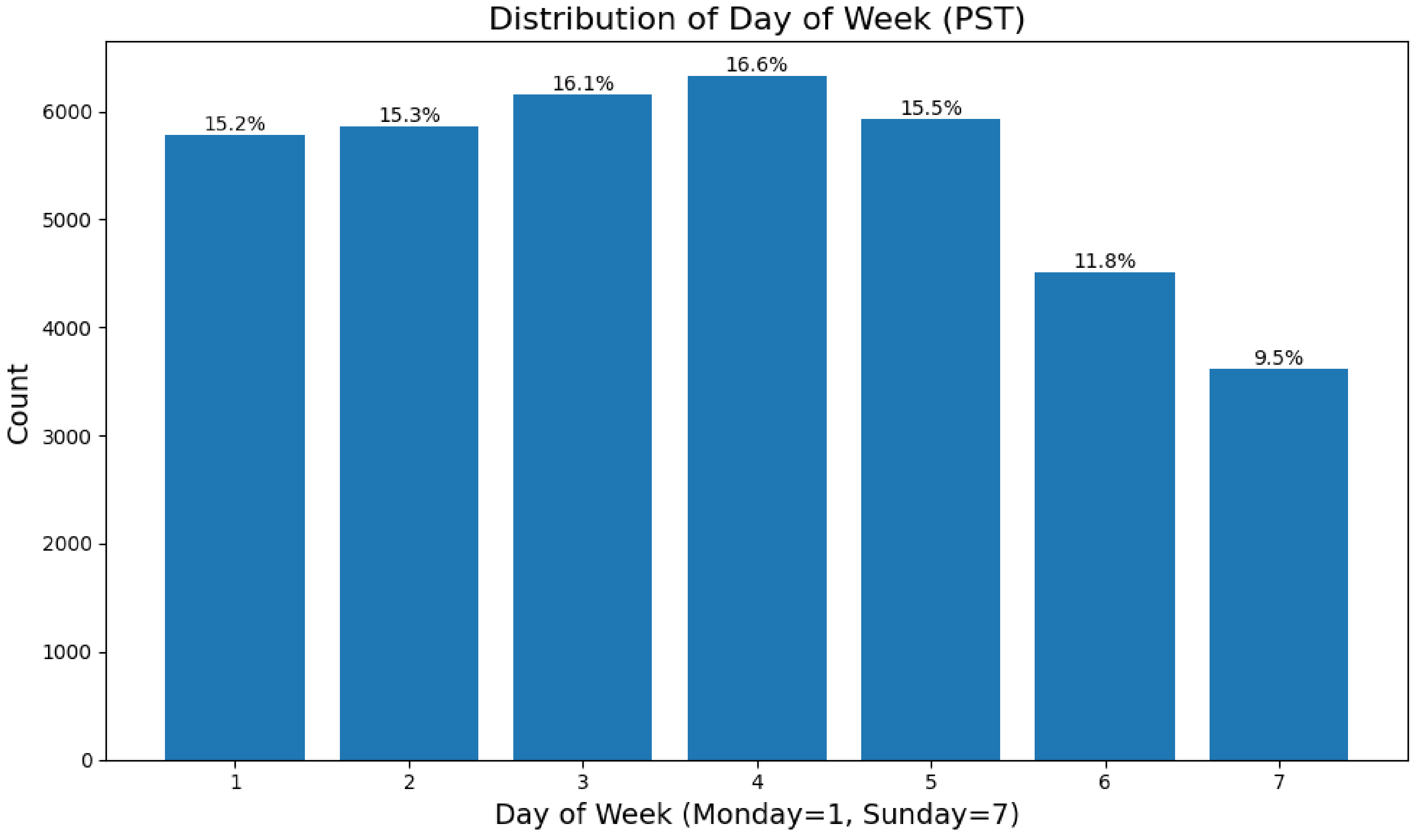


Figure 3: The Distribution of Reels based on the Time of Day in PST before Merging

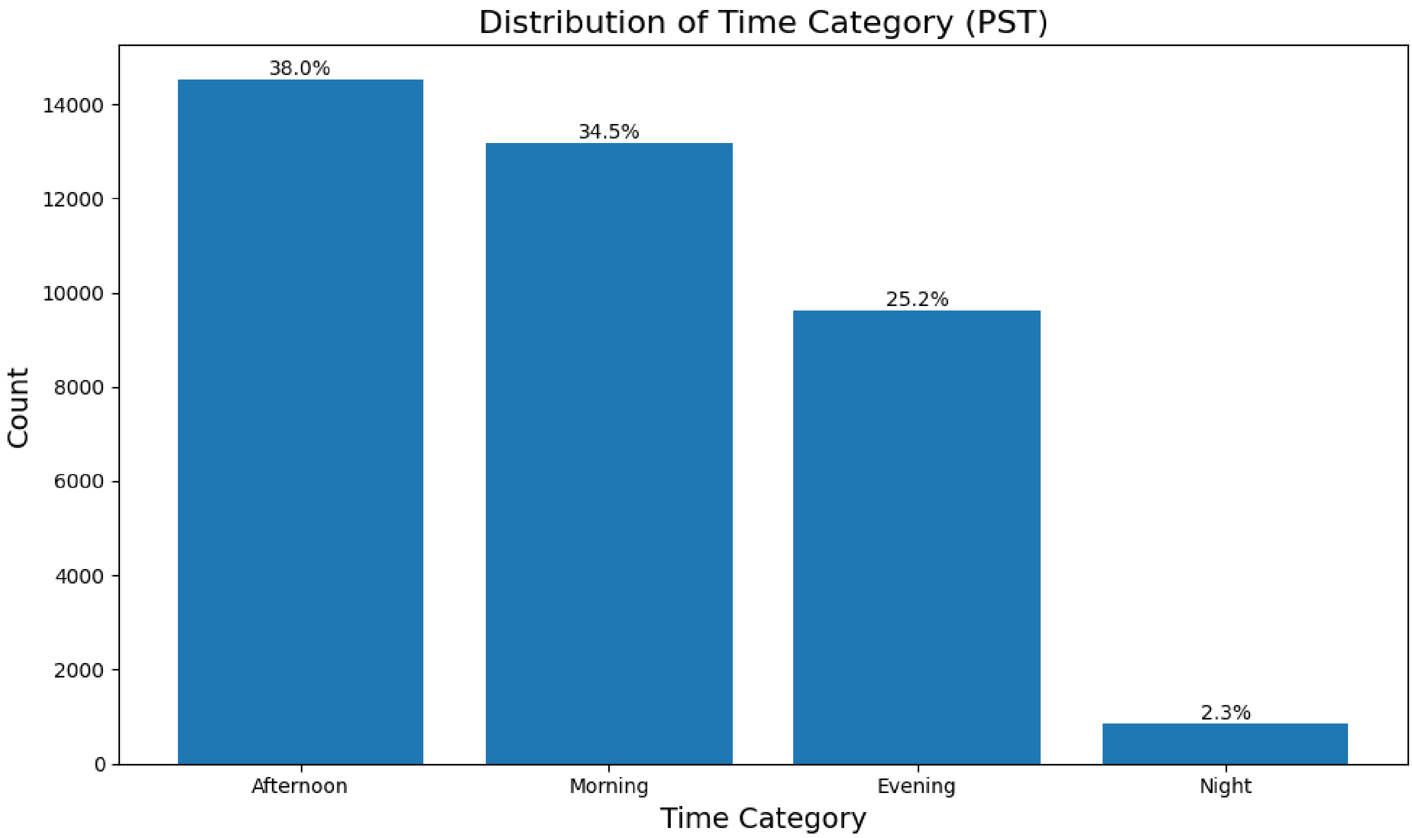

Figure 4: The Distribution of Reels based on the Time of Day in PST after Merging

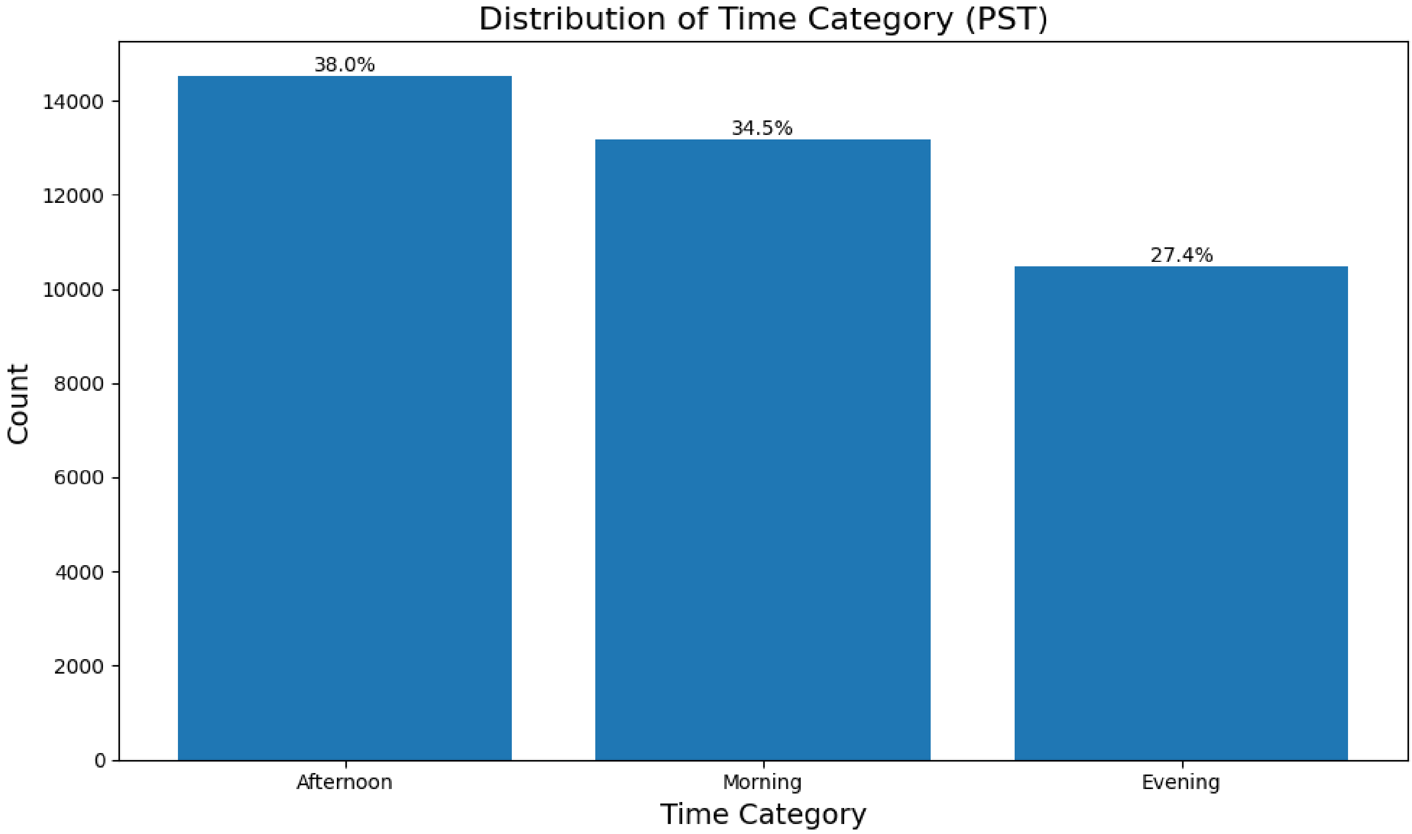


Figure 5: The Proportion of Missing Video Views Across Time Elapsed in Days

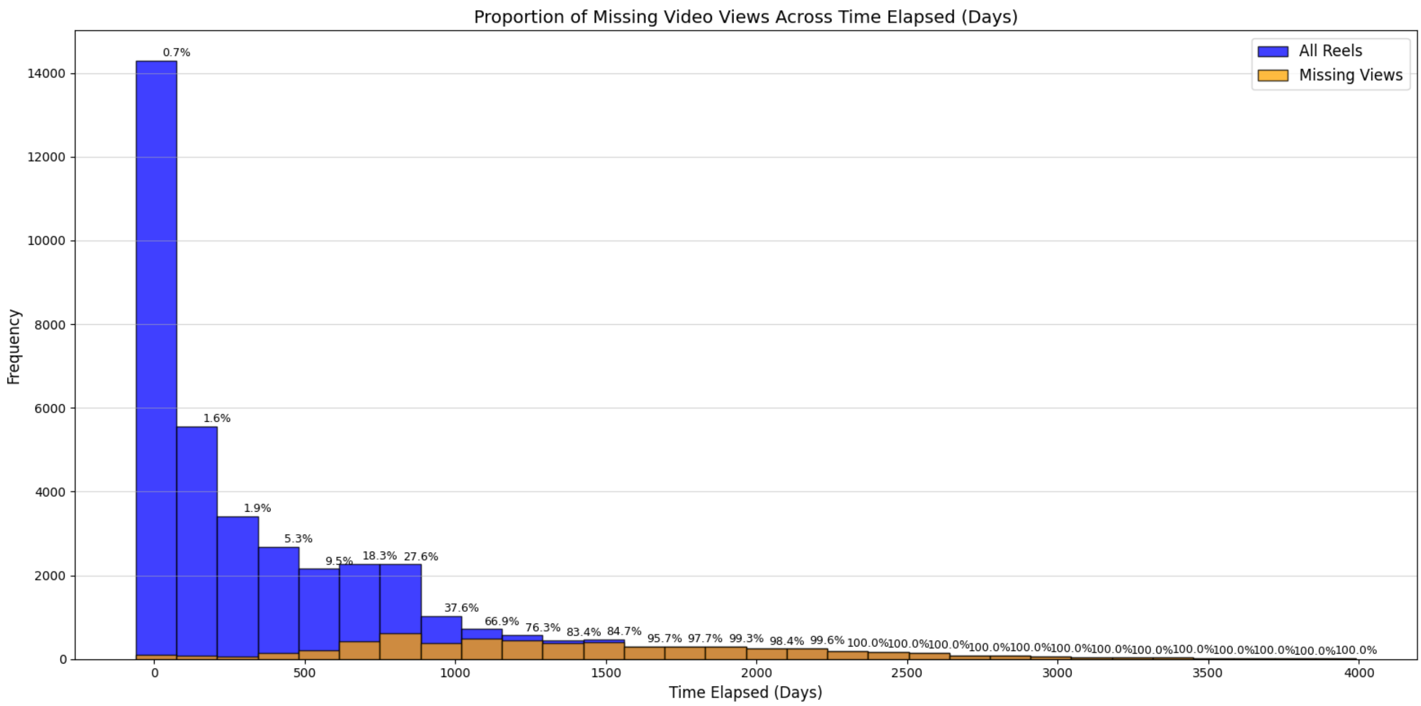

Figure 6: Feature Correlation with Views Count for the Random Forest Imputation Model

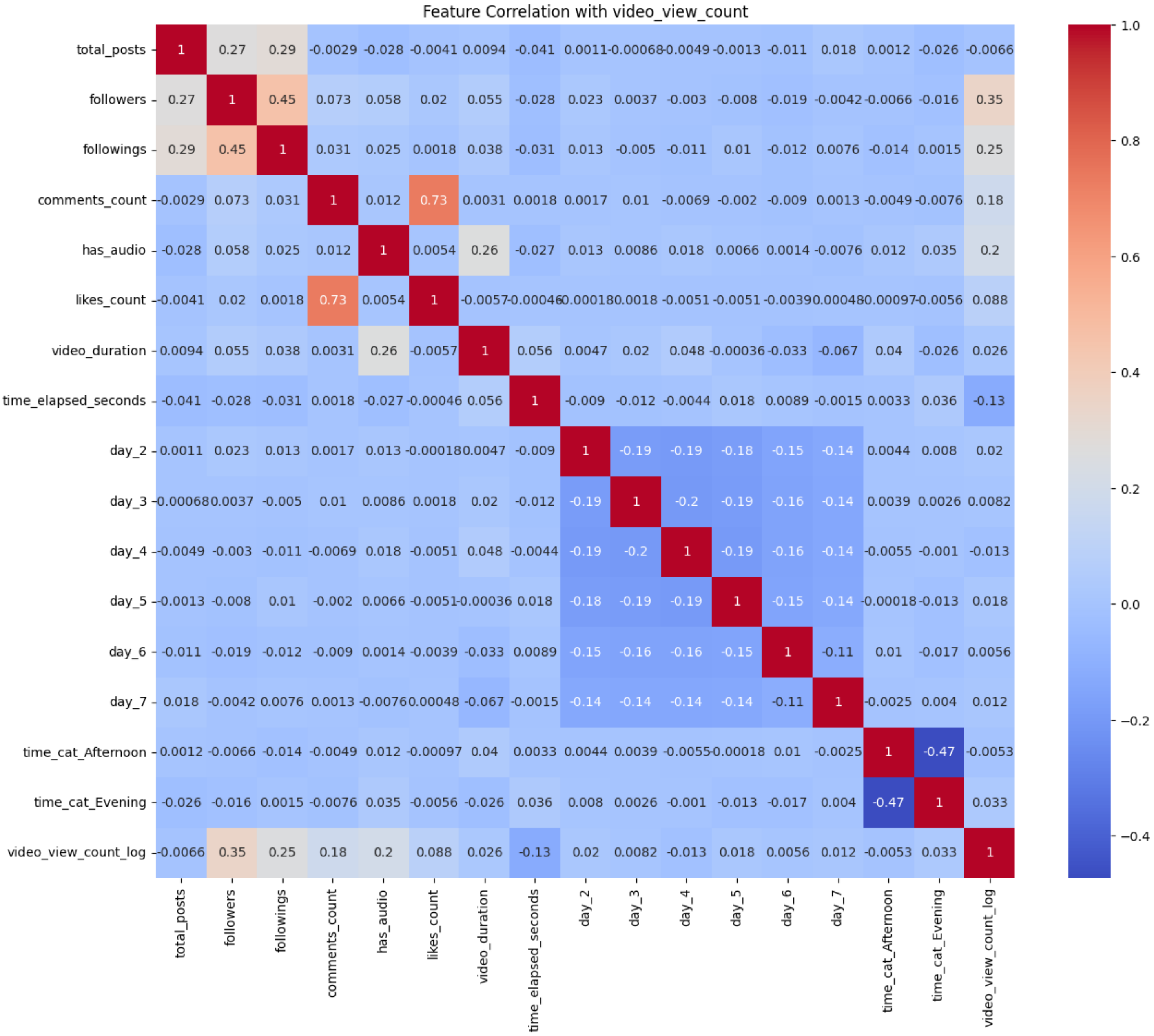

Figure 7: Residuals Analysis for the Random Forest Imputation Model

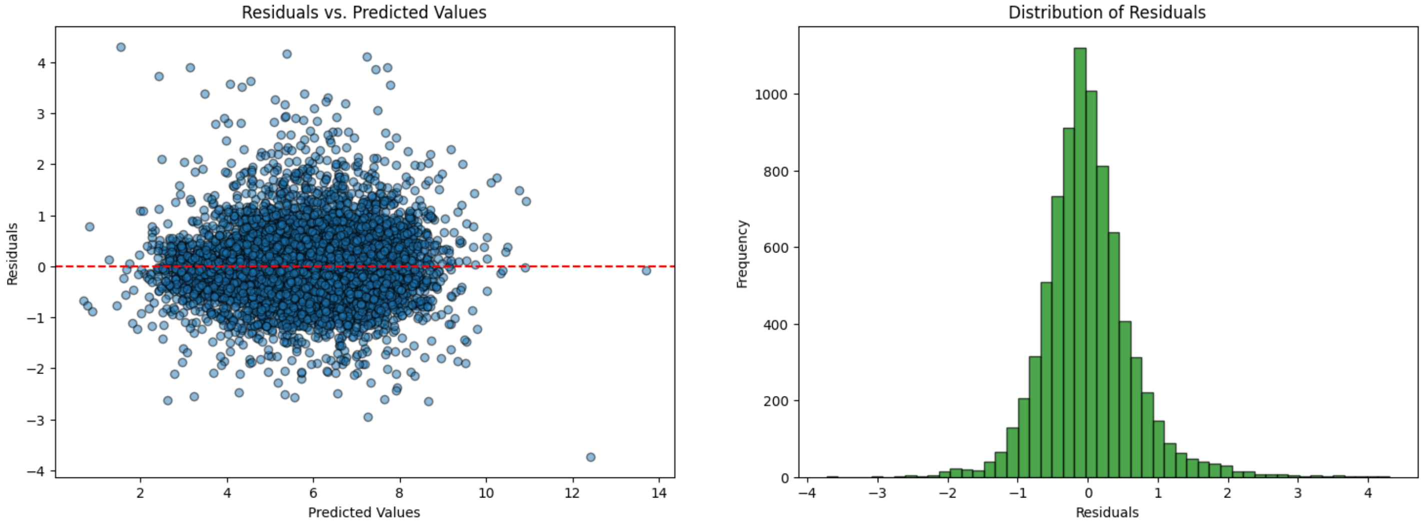


Figure 8: The Distribution of EPF and Log-Transformed EPF

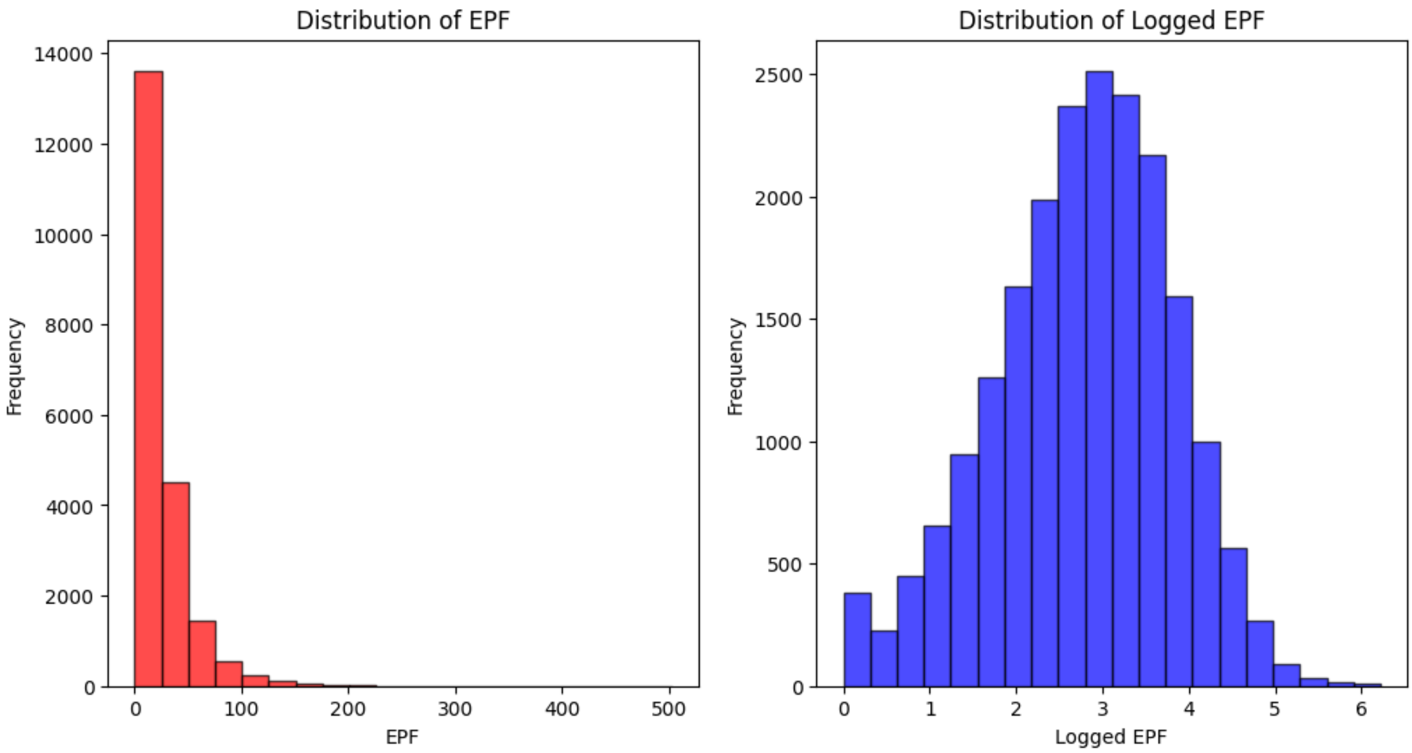

Figure 9: Heatmap of the Means of Logged EPF by Day and Time

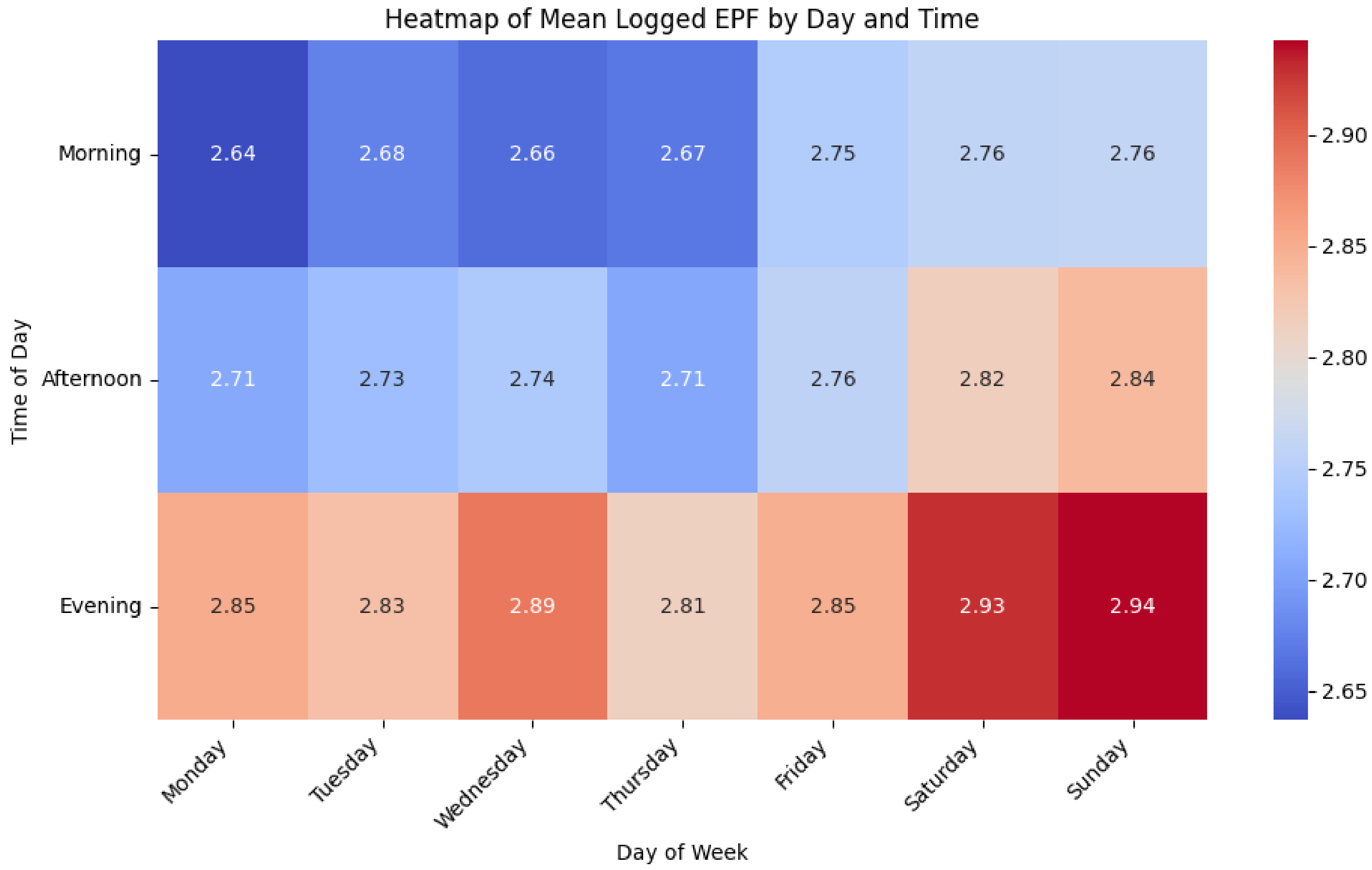


Figure 10: Mean Logged EPF Over Days and Times (Sequential)

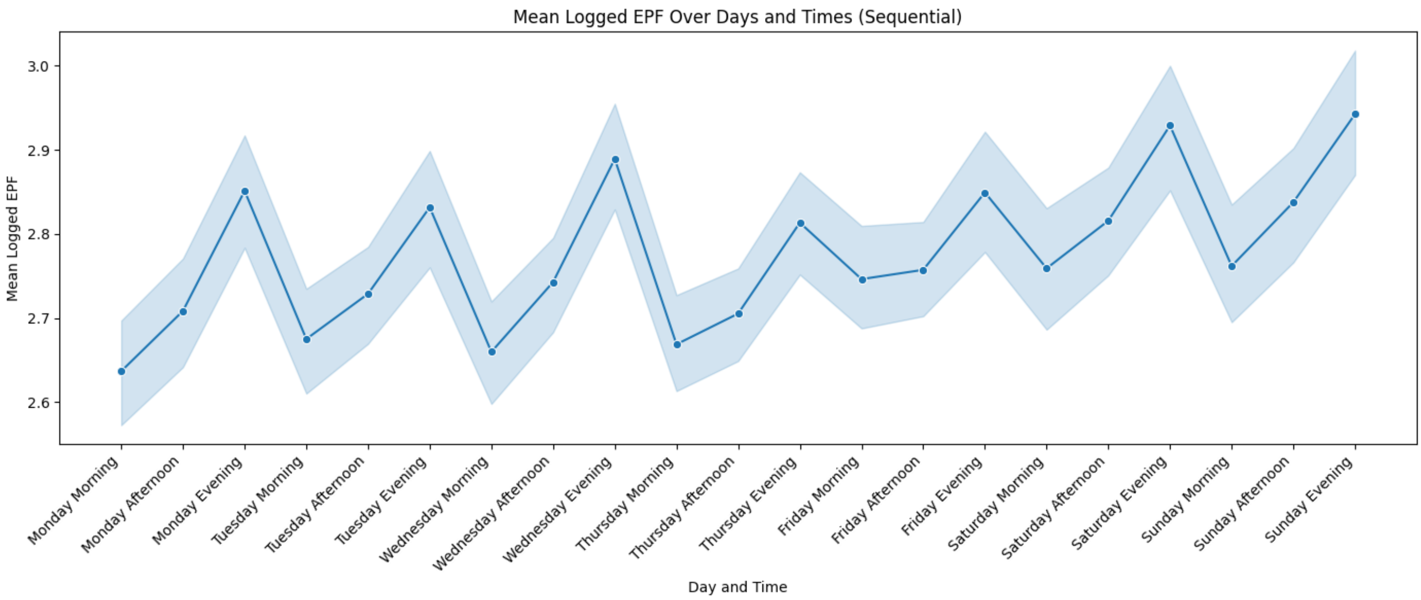

Figure 11: Results of ANOVA Residual Analysis