Statistical Insights into User Feedback: A Study of Reviews and Ratings in Messaging Apps

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***Abstract*—The rapidly expanding mobile app market has increased competition, making effective e-business strategies increasingly important for success. This study focuses on the Vietnam region and uses Google Play Store research to gain insights for software companies, especially those developing texting and messaging applications. By collecting and analyzing app rating data from Google Play Store, we analyze average app ratings to identify influential factors, perform descriptive statistical analysis to compare competing applications in the same category. Furthermore, we present an advanced time series prediction model, such as Autoformer and PatchTST, to predict future rating trends. Our findings highlight important success factors, recommend strategies, and identify potential risks to avoid. The goal of this insight is to help companies improve app design, increase user satisfaction, manage competitive performance, and achieve sustainable growth in a competitive marketplace.**

***Index Terms*—Mobile apps, User feedback, Reviews, Ratings, Descriptive statistics, Time series prediction, Autoformer, PatchTST.**

I. Introduction

Messaging applications are central to digital communication, particularly within Vietnam's growing e-business sector. As competition intensifies, user feedback—comprising reviews and ratings—has become a crucial factor for app developers aiming to optimize product performance and user satisfaction. This study, *Statistical Insights into User Feedback: A Study of Reviews and Ratings in Messaging Apps*, explores user reviews and ratings from Vietnam's messaging app market to identify trends and factors influencing user sentiment.

We apply advanced deep learning models, namely Autoformer and PatchTST, to analyze temporal feedback patterns. These models, known for their effectiveness in long-term forecasting, offer enhanced capabilities for capturing non-linear and dynamic trends in user data. Using evaluation metrics such as Mean Absolute Error (MAE), Mean Root Squared Error (MRSE), and Relative Squared Error (RSE), we aim to derive actionable insights into user preferences and predict future app ratings. Our findings are intended to help businesses improve app design, increase user satisfaction, and foster sustainable growth in a competitive marketplace.

II. Related Works

Recent advances in deep learning have revolutionized time-series forecasting, surpassing traditional methods like ARIMA and linear regression in predictive accuracy. Autoformer, introduced by Wu et al. (2021) [1], leverages a decomposition architecture to separately model trend and seasonal components, improving long-term forecasting performance. Additionally, Autoformer's attention mechanism allows it to capture long-range dependencies and reduce noise effects, making it highly effective for analyzing customer feedback.

Similarly, PatchTST, proposed by Nie et al. (2022) [2], enhances time-series forecasting by dividing data into smaller patches, inspired by Vision Transformers. This approach enables PatchTST to capture both local and global patterns, offering superior flexibility in modeling irregular or seasonal variations in user feedback. Compared to traditional models like LSTM and GRU, PatchTST is better suited for handling complex feedback data structures, making it particularly useful for sentiment analysis in e-business platforms.

Both Autoformer and PatchTST outperform traditional models in terms of accuracy, as measured by metrics like MAE and RMSE. These models represent state-of-the-art approaches in time-series analysis, providing detailed insights into user behavior and preferences, which are essential for optimizing messaging apps in a competitive market.

III. Methods

A. Materials

The data used in this study was scraped from Google Play Store using Python. The dataset covers the period from January 1, 2020, to October 31, 2024. It consists of user reviews and ratings for two messaging applications: Messenger and Snapchat. Data cleaning was performed to remove any incomplete or empty entries, ensuring a reliable dataset for analysis.

	A	B	C	D	E	F
1	userName	score	content	at	thumbsUp	reviewCreatedVersion
2	NgÆ°á»i d	5	Tá»‘t	30/10/2024	1	481.1.0.74.109
3	NgÆ°á»i d	5	oke	30/10/2024	0	481.1.0.74.109
4	NgÆ°á»i d	1	Mess nhÆ	30/10/2024	0	481.1.0.74.109
5	NgÆ°á»i d	1	Mess khÃ´	30/10/2024	0	452.0.0.50.109

Fig. 1: Messenger dataset includes 6 columns and 381,840 rows

	A	B	C	D	E	F
1	userName	score	content	at	thumbsUp	reviewCreatedVersion
2	NgÆ°á»i d	4	Tháº¥y cu	27/10/2024	4	13.13.0.36
3	NgÆ°á»i d	5	Emoi story	24/10/2024	6	13.12.0.37
4	NgÆ°á»i d	1	báº£n Ä‘á	24/10/2024	29	13.13.0.36
5	NgÆ°á»i d	1	Minh ns v	20/10/2024	19	13.12.0.37

Fig. 2: Snapchat dataset includes 6 columns and 4,665 rows

B. Descriptive Statistics

1) Mean: The *mean* (average) is the sum of all data points divided by the number of data points. Formula:

$$\text{Mean} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

where x_i is each data point and N is the total number of data points.

2) Median: The *median* is the middle value when the data points are arranged in ascending order. If the number of data points is even, the median is the average of the two middle numbers.

3) Mode: The *mode* is the value that appears most frequently in the dataset. If no value repeats, the dataset is said to have no mode.

4) Range: The *range* is the difference between the maximum and minimum values in the dataset. Formula:

$$\text{Range} = \text{Max}(x) - \text{Min}(x)$$

5) Variance: *Variance* measures how much the data points deviate from the mean. Formula:

$$\text{Variance} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$$

where μ is the mean of the dataset.

6) Standard Deviation: *Standard deviation* is the square root of the variance and represents the spread of data points. Formula:

$$\sigma = \sqrt{\text{Variance}}$$

7) Histogram: A *histogram* is a graphical representation of the distribution of a dataset, showing the frequency of data points within specific intervals or bins.

8) Box Plot: A *box plot* displays the distribution of data based on a five-number summary: minimum, first quartile, median, third quartile, and maximum.

9) Scatter Plot: A *scatter plot* is a graph that uses Cartesian coordinates to display values for two variables, helping to identify relationships between them.

C. Inferential Statistics

1) t-Test: A *t-test* is used to compare the means of two groups to determine if they are statistically significantly different. Formula for a one-sample t-test:

$$t = \frac{\bar{x} - \mu_0}{\frac{s}{\sqrt{N}}}$$

where $\bar{x}$ is the sample mean, μ_0 is the population mean, s is the sample standard deviation, and N is the sample size.

2) Chi-Square Test: The *chi-square test* assesses whether there is a significant association between two categorical variables. Formula:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

where O_i is the observed frequency and E_i is the expected frequency.

3) Confidence Interval: A *confidence interval* is a range of values that is likely to contain the true population parameter. Formula for a confidence interval for the mean:

$$\left(\bar{x} - Z\frac{s}{\sqrt{N}}, \bar{x} + Z\frac{s}{\sqrt{N}}\right)$$

where Z is the Z-score for the desired confidence level, $\bar{x}$ is the sample mean, s is the sample standard deviation, and N is the sample size.

D. Temporal Analysis

Temporal analysis tracks trends and changes in data over time. To analyze the user ratings and review activity over time:

- Aggregate score by month: Calculate the average monthly ratings by grouping data by the "at" (date) column.
- Plot the trend: Use time series plots to observe changes in user satisfaction over time.
- Identify seasonal patterns: Analyze for any repeating cycles or anomalies in the review frequency or score.

E. Autoformer Model

Autoformer is a time series forecasting model that relies on the Series Decomposition Block to break down historical data into trend and seasonal components [1].

1) Series Decomposition Block: Autoformer decomposes the input time series X into two components:

a) Trend Component (X_t): The trend component captures long-term patterns by smoothing out periodic fluctuations. It is computed using a moving average over the input series:

$$X_t = \text{AvgPool}(\text{Padding}(X))$$

where X is the input series and Padding ensures proper handling of edge effects.

b) Seasonal Component (X_s): The seasonal component captures short-term periodic fluctuations by subtracting the trend component from the original data:

$$X_s = X - X_t$$

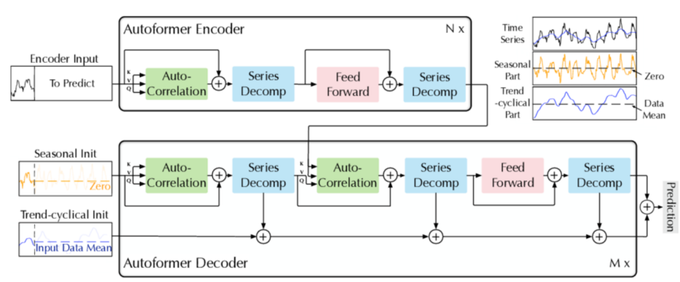

Fig. 3: Architecture of Autoformer

2) Model Blocks: Autoformer consists of the following key blocks:

- Series Decomposition Block: Separates the input series into trend and seasonal components.
- Auto-Correlation Block: Detects repeating patterns by analyzing relationships between different time steps.
- Feed Forward Block: Refines the trend and seasonal components and combines them to generate the final prediction.

3) Encoder and Decoder: The encoder extracts long-term trends and short-term seasonal patterns from the input data. It applies the Series Decomposition Block multiple times to decompose the data iteratively. The decoder reconstructs future values based on the encoder's output. Like the encoder, the decoder uses the Series Decomposition Block to refine its predictions.

F. PatchTST Model

PatchTST is a transformer-based model designed for multivariate time series forecasting. It processes the input data in patches (small segments) to efficiently capture trends and temporal dependencies [2].

1) Model Overview: PatchTST processes multi-variate time series data by splitting each variable (channel) into independent streams, which are then processed using a transformer encoder.

a) Input Data: The input consists of multi-variate time series X, where each variable X_m represents a distinct time series. For example, sales data, temperature readings, or stock prices over time.

b) Channel Independence: Each variable X_m is processed independently at first, breaking the input into M separate streams for each variable.

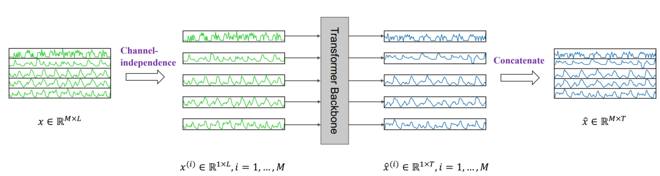

Fig. 4: PatchTST Model Overview

2) Transformer Backbone: The transformer backbone in PatchTST consists of the following steps:

- Instance Normalization and Patching: Normalizes the input data and splits the time series into small patches.
- Projection and Position Embedding: Adds positional information to the patches to preserve the order of time steps.
- Transformer Encoder: Uses multi-head attention to learn relationships between patches and a feed-forward network to refine these relationships.
- Flatten and Linear Head: Combines the output of the transformer encoder and applies a linear layer to produce the final predictions for each variable.

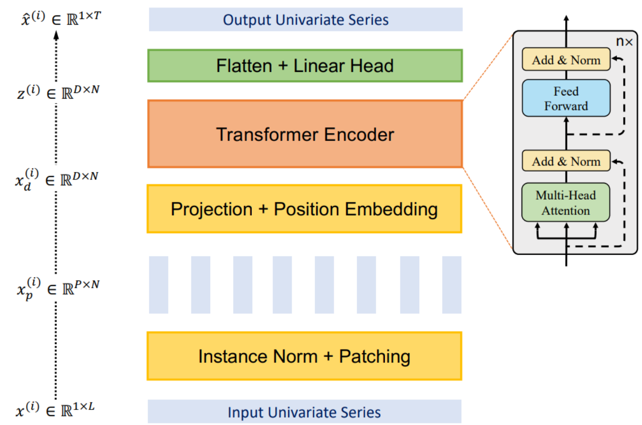

Fig. 5: Transformer Backbone (Supervised)

3) Self-Supervised Transformer Backbone: PatchTST also supports a self-supervised learning approach. In this version, some input patches are masked, and the model is trained to reconstruct the masked patches, allowing it to learn useful features even in the absence of labeled data.

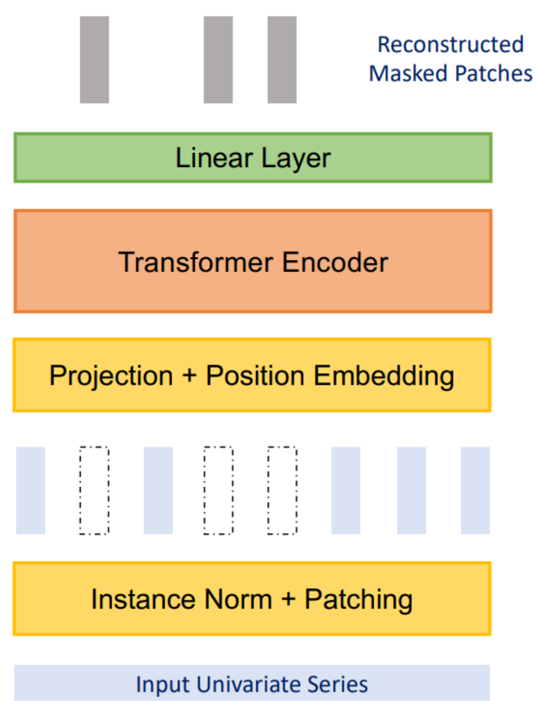

Fig. 6: Transformer Backbone (Self-supervised)

IV. Results and Discussion

A. Descriptive Statistics

1) Messenger: From the descriptive statistics for Messenger, we can observe that the mean score (2.774) suggests that, on average, users tend to rate the application slightly above the middle of the scale. The median score of 2.0 and the mode score of 1 both indicate that a significant proportion of users rate the application lower, particularly clustered around 1, which could indicate a high frequency of lower ratings. The range of scores is 4, suggesting that the data spans a wide spectrum of ratings. The variance (3.359) and standard deviation (1.833) further suggest considerable variability in the ratings, reflecting diverse opinions and experiences among users.

Statistic	Value
Mean Score	2.774232071632285
Median Score	2.0
Mode Score	1
Range of Scores	4
Variance of Scores	3.3591476599909016
Standard Deviation of Scores	1.8327977684378878

TABLE I: Descriptive statistics for Messenger ratings.

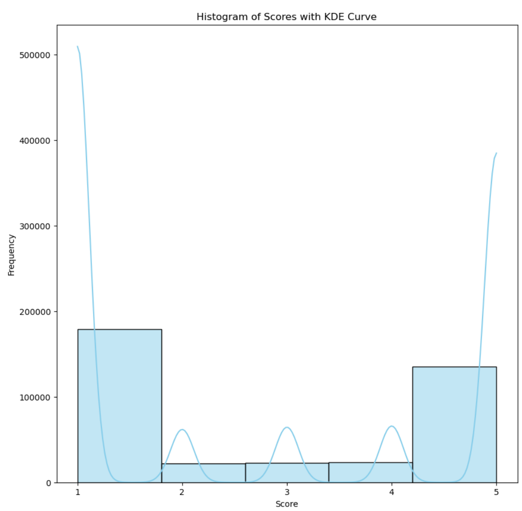

Fig. 7: Histogram with KDE of Messenger dataset

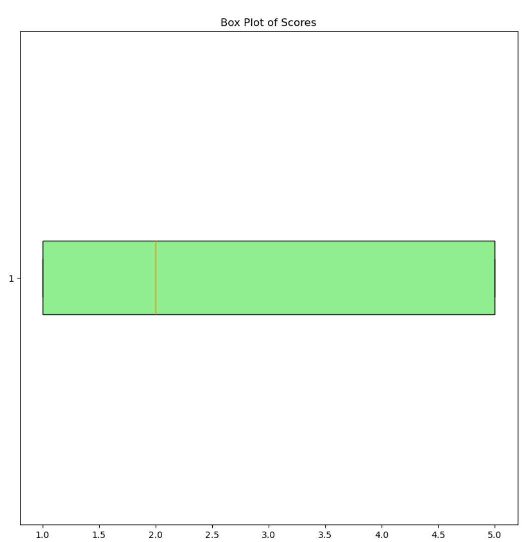

Fig. 8: Box Plot of Messenger dataset

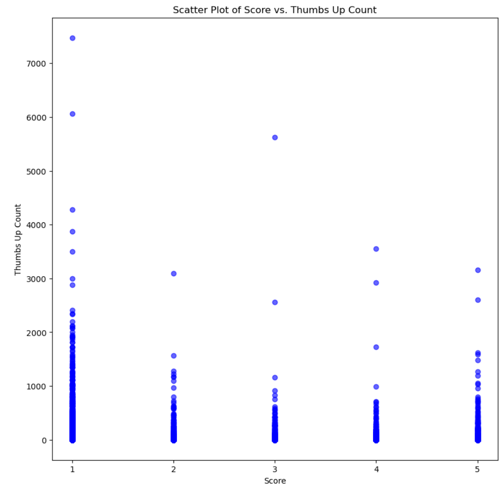

Fig. 9: Scatter Plot with Discrete Axes of Messenger dataset

2) Snapchat: For Snapchat, the mean score of 2.0154 indicates that the average user rating is slightly above the lowest possible score, suggesting a generally negative reception from users. The median score (1.0) and mode score (1) both suggest that the most common rating is the lowest score, indicating that a substantial number of users are dissatisfied with the application. Like Messenger, Snapchat has a range of scores of 4, showing a wide spread of ratings. The variance (2.747) and standard deviation (1.657) are lower than Messenger's, suggesting somewhat less variability in the scores compared to Messenger, but still indicating a notable diversity of user opinions.

Statistic	Value
Mean Score	2.0154373927958833
Median Score	1.0
Mode Score	1
Range of Scores	4
Variance of Scores	2.7473490258885787
Standard Deviation of Scores	1.6575129036869

TABLE II: Descriptive statistics for Snapchat ratings.

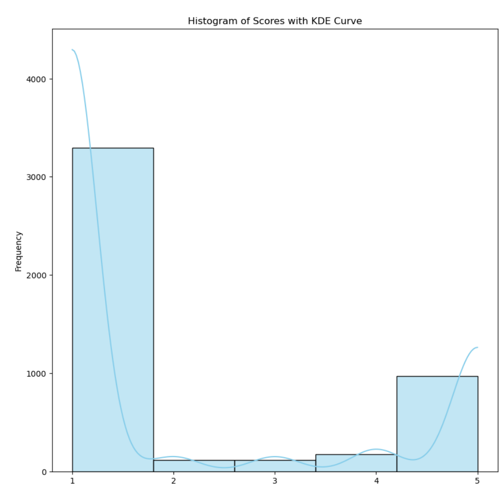

Fig. 10: Histogram with KDE of Snapchat dataset

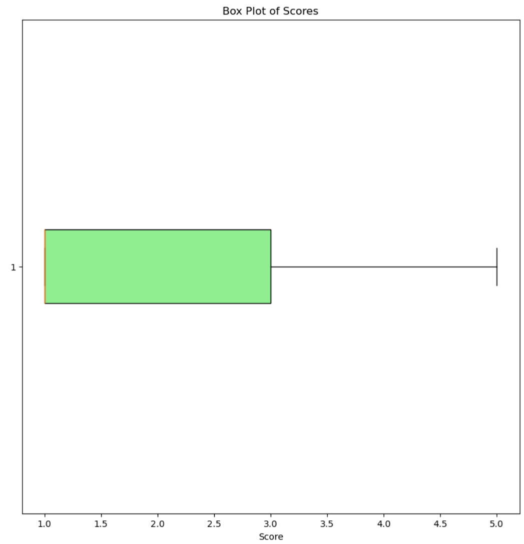

Fig. 11: Box Plot of Snapchat dataset

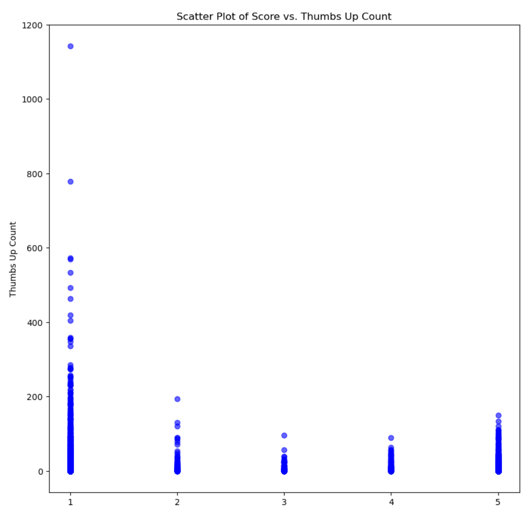

Fig. 12: Scatter Plot with Discrete Axes of Snapchat dataset

3) Comment about trends in user ratings and app reviews: The tendency for Vietnamese users to rate primarily with 1-star or 5-star ratings on platforms like Google Play can be attributed to several psychological, cultural, and practical factors. First, emotional polarization plays a significant role. People are more likely to leave reviews when they have strong feelings about their experience. A 1-star rating typically reflects frustration, dissatisfaction, or anger over issues such as bugs, crashes, or unmet expectations. On the other hand, a 5-star rating signifies satisfaction, appreciation, or enthusiasm for an app's performance or features. Neutral or moderate experiences, which might warrant 2, 3, or 4 stars, often lack the emotional impact to motivate users to leave feedback.

Cultural tendencies also influence this behavior. In Vietnam, feedback is often expressed decisively, with a preference for clear, extreme opinions rather than moderate ones. This could stem from a belief that middle-ground ratings fail to convey the full weight of the user's experience. Additionally, exaggeration might be seen as a way to ensure their opinions are noticed or to align with social norms of expressing feedback more vividly.

The perception of rating systems further contributes to this polarization. Many users may not fully understand or utilize the nuanced differences between intermediate ratings. For instance, they might view 1 star simply as "bad" and 5 stars as "good," while 2, 3, or 4 stars feel unnecessary or less impactful. Similarly, users who want to send a clear message to developers may feel that extreme ratings (1 or 5 stars) are more effective in drawing attention to their feedback, whether it is to highlight a significant issue or to show strong appreciation. Moreover, mobile platforms like Google Play may amplify this bias towards extremes. Reviews with 1-star or 5-star ratings are often more visible or perceived as more influential, leading users to subconsciously adopt this trend. Without clear incentives or guidance from the platform or developers to leave more nuanced feedback, users may default to these extremes. This lack of encouragement for detailed feedback can further skew the rating distribution.

B. Inferential Statistics

1) Welch Two Sample t-test: The Welch Two Sample t-test was conducted to compare the mean ratings between Messenger and Snapchat. This test is used when the two groups may have unequal variances and/or unequal sample sizes. It adjusts the degrees of freedom to account for these differences, providing a more accurate comparison of the means.

Statistic	**Value**
t-statistic	-2.9717
df (degrees of freedom)	104.2
p-value	0.003677
95% Confidence Interval	[-0.6733, -0.1344]

TABLE III: Welch Two Sample t-test results comparing Messenger and Snapchat.

The t-test results show a t-statistic of -2.9717 with a p-value of 0.003677, which is less than the significance level of 0.05. This indicates a statistically significant difference between the two groups. The 95% confidence interval for the difference in means ranges from -0.6733 to -0.1344, indicating that the mean rating for Messenger is significantly lower than for Snapchat.

2) Confidence Interval for Mean Ratings: The 95% confidence intervals for the mean ratings of Messenger and Snapchat are as follows:

App	**Mean**	**Lower 95% CI**	**Upper 95% CI**
Messenger	2.8353	2.6751	2.9955
Snapchat	3.2391	3.0192	3.4591

TABLE IV: Confidence intervals for the mean ratings of Messenger and Snapchat.

The confidence intervals indicate that the mean rating for Messenger is between 2.6751 and 2.9955, while for Snapchat, it is between 3.0192 and 3.4591. This further confirms that Snapchat has a higher mean rating compared to Messenger.

3) Contingency Table for Rating Categories: We categorized the ratings into two groups: ’High’ for ratings of 3 or above, and ’Low’ for ratings below 3. The distribution of these categories for each app is shown below:

Rating Category	Messenger	Snapchat
High	23	42
Low	35	16

TABLE V: Distribution of High and Low ratings for Messenger and Snapchat.

From the contingency table, we observe that Messenger has more ’Low’ ratings (35) compared to ’High’ ratings (23). On the other hand, Snapchat has more ’High’ ratings (42) than ’Low’ ratings (16).

4) Pearson’s Chi-squared Test with Yates’ Continuity Correction: A Pearson’s Chi-squared test with Yates’ continuity correction was performed to assess the association between the app and the rating category (High vs. Low). The results are:

Statistic	Value
Chi-squared	11.338
Degrees of freedom	1
p-value	0.0007596

TABLE VI: Pearson’s Chi-squared test with Yates’ continuity correction for rating categories.

The p-value of 0.0007596 is less than 0.05, indicating a statistically significant relationship between the app type and the rating category. This suggests that the type of app has a significant impact on whether users rate it as ’High’ or ’Low’.

C. Temporal Analysis

1) Messenger:

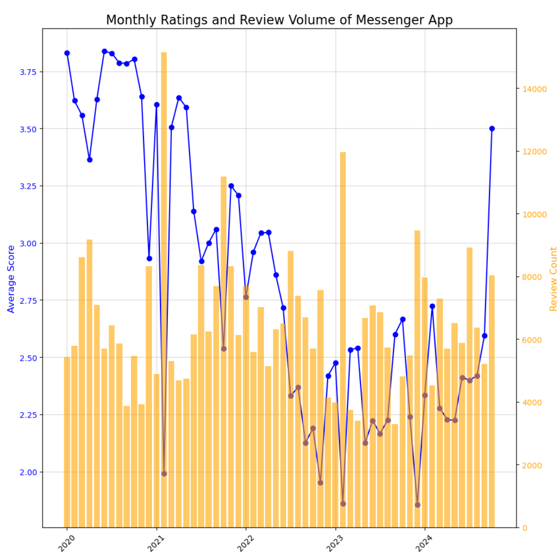

Fig. 13: Chart of Monthly Ratings and Review Volume of the Messenger App

The controversy surrounding the messaging app in Vietnam was more than just a temporary setback; it underscored the broader challenges tech companies face when managing user-generated content across diverse cultural landscapes. In this case, the offense was particularly severe due to Ho Chi Minh’s revered status as a national hero and a symbol of independence and unity in Vietnam. The app’s failure to anticipate how content could be perceived in a highly sensitive cultural context exposed significant vulnerabilities in its content management system.

The reliance on third-party providers for GIFs and other media meant that the app had limited control over the quality and appropriateness of content circulating on its platform. While the app’s response included stricter moderation and public apologies, the backlash illustrated how quickly user trust can erode, especially when a platform fails to prevent harmful content from reaching its audience in the first place.

This incident also highlighted the importance of cultural awareness in global operations. Companies must understand local customs, values, and sensitivities to avoid missteps. In the long term, companies must prioritize not only reactive measures but also preventive systems, such as region-specific content filters, AI-powered content review, and local community engagement, to ensure that such issues do not resurface and to preserve user loyalty.

2) Snapchat:

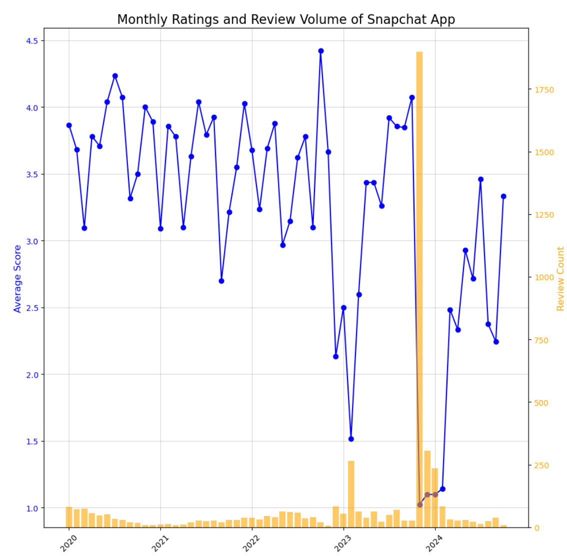

Fig. 14: Chart of Monthly Ratings and Review Volume of the Snapchat App

Snapchat’s success in Vietnam has been largely due to its strategic focus on staying neutral in politically sensitive matters while catering to local cultural preferences. This approach allowed the platform to build a loyal user base, especially among the younger demographic, who value privacy and visually engaging experiences. Features such as AR filters for Lunar New Year, which resonate deeply with Vietnamese cultural traditions, contributed significantly to its widespread adoption. During the COVID-19 pandemic, when digital communication became essential, Snapchat's privacy-centric and dynamic interface allowed it to maintain strong engagement, further strengthening its position in a competitive social media landscape.

However, Snapchat faced significant challenges in 2022 that tested its resilience in the Vietnamese market. The decision to remove the Hoang Sa and Truong Sa islands from its map was a major misstep. This action, perceived as an omission of Vietnam's territorial claims in the South China Sea, sparked outrage among Vietnamese users. The subsequent four-month decline in ratings, driven by calls to boycott the platform, demonstrated the sensitivity of such geopolitical issues and the potential consequences for global brands. Although Snapchat later restored the islands to its map and issued a public clarification, the delay in addressing the issue exposed vulnerabilities in its crisis management approach, especially in geopolitically sensitive regions.

Further controversy arose with Snapchat's decision to shut down Zenly in 2022, a popular social location-sharing app that had a loyal Vietnamese user base. Many users saw this as an attempt to eliminate competition and consolidate features into Snapchat's ecosystem. The integration of Zenly-like features into Snapchat, while intended to streamline user experience, was met with criticism for poor usability. The backlash led to another dip in ratings, but Snapchat's continued iterative improvements to the new features by mid-2023 gradually regained user trust. This situation highlighted the importance of thoughtful integration and prompt responsiveness to user feedback following acquisitions or product changes, especially in competitive markets like Vietnam.

D. Autoformer

1) Snapchat:

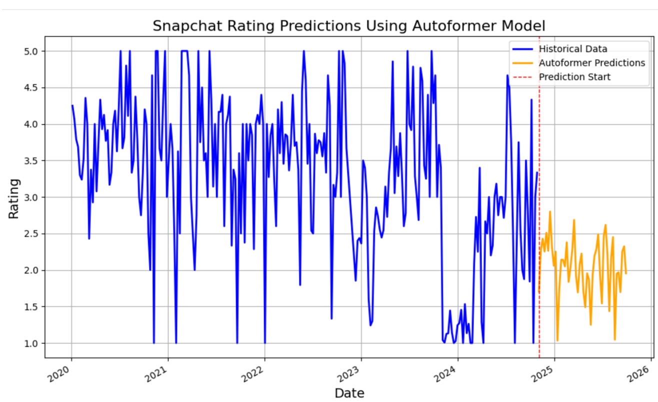

Fig. 15: Plot graph of Autoformer perform forecasting on Snapchat time series data

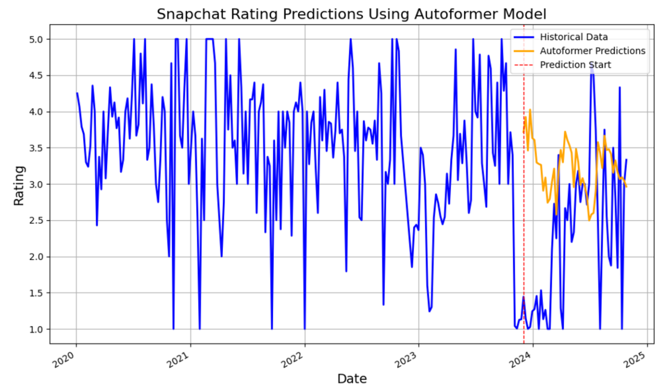

Fig. 16: Plot graph of validation on Autoformer when perform forecasting on Snapchat time series data

The historical Snapchat rating data shows long-term consistency, with ratings fluctuating within a stable range. However, a recent anomaly introduced significant variability, disrupting this stability. This anomaly likely signals a structural change in the data's behavior, which the Autoformer model identifies. Autoformer, designed for time series forecasting, captures long-term dependencies and trends effectively. Based on the historical pattern of rapid changes within a consistent range, the model predicts continued fluctuations but with a reduced level of consistency, reflecting the anomaly's potential long-term impact. The model anticipates variability but does not return to the prior stable trend due to the weight it assigns to recent significant deviations.

2) Messenger:

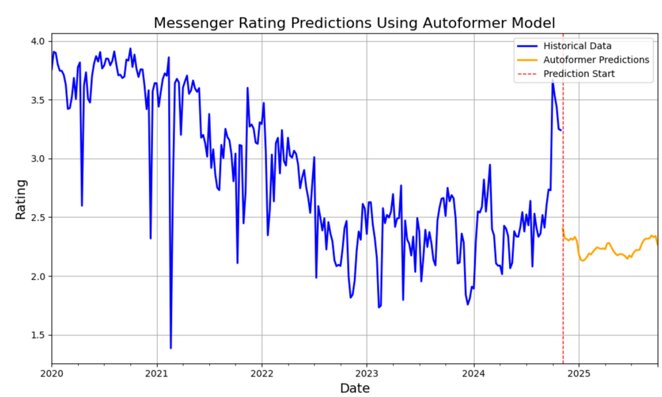

Fig. 17: Plot graph of Autoformer perform forecasting on Messenger time series data

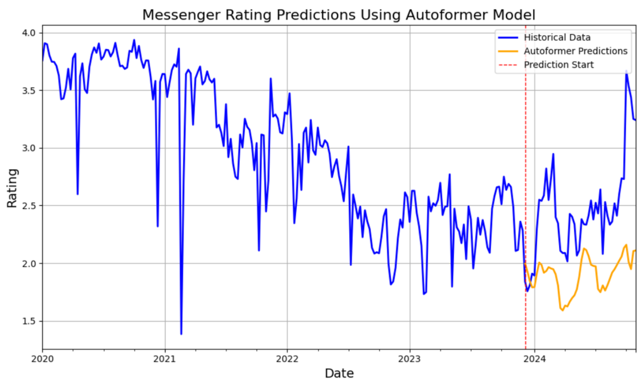

Fig. 18: Plot graph of validation on Autoformer when perform forecasting on Messenger time series data

Autoformer takes a holistic approach by analyzing the entire historical dataset, which can make it less responsive to sudden changes or anomalies. In the case of the Messenger dataset, the historical data shows a pattern of quick recovery following drops in ratings and a consistent ability to maintain an overall stable average rating.

Given this long-term consistency, Autoformer predicts that Messenger's ratings will stabilize within half a year, aligning with its historical trend of resilience and recovery. This reflects Autoformer's strength in capturing overarching patterns but its limitations in adapting to abrupt deviations.

E. PatchTST

1) Snapchat:

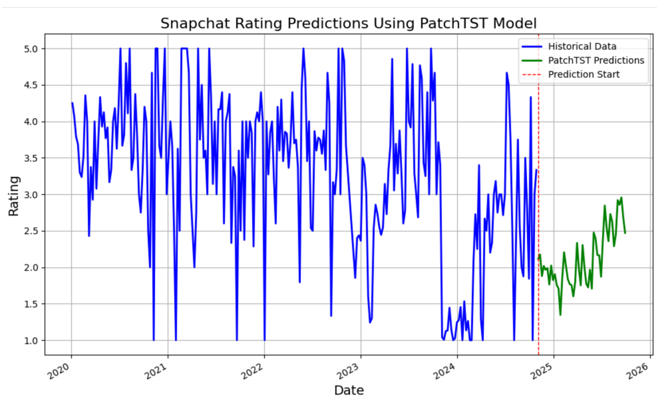

Fig. 19: Plot graph of PatchTST perform forecasting on Snapchat time series data

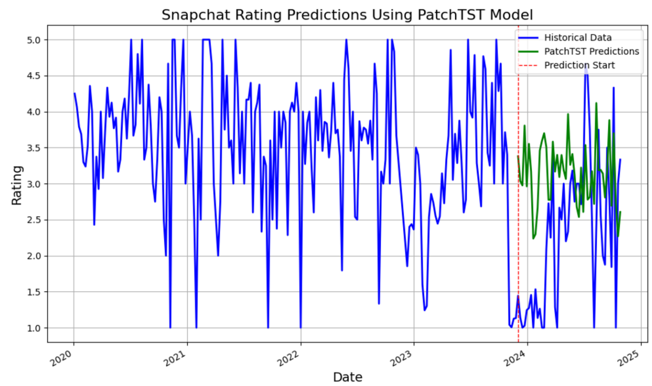

Fig. 20: Plot graph of validation on PatchTST when perform forecasting on Snapchat time series data

PatchTST employs a unique methodology compared to Autoformer, focusing more on recent data by segmenting it into smaller chunks for deep learning. This allows it to capture localized patterns effectively, particularly in periods of high variability.

Given the recent anomaly, PatchTST places significant emphasis on these segments, identifying a potential recovery pattern based on prior trends. The model predicts that the ratings will rebound and follow an upward trajectory, resembling the recovery observed in earlier anomalies. This approach highlights PatchTST's sensitivity to recent changes, enabling it to detect and project short- to medium-term trends with greater precision.

2) Messenger:

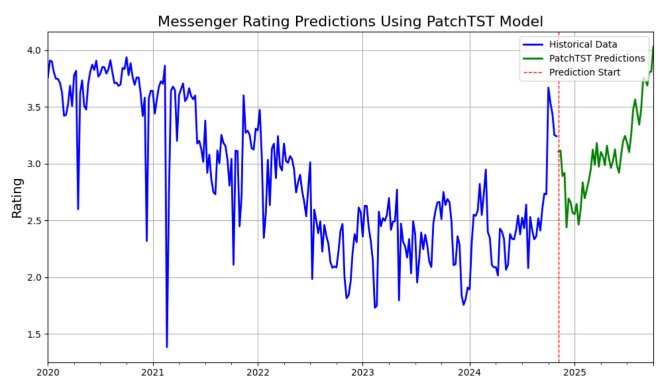

Fig. 21: Plot graph of PatchTST perform forecasting on Snapchat time series data

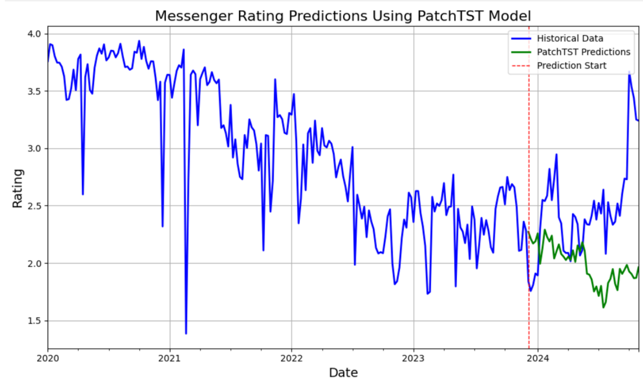

Fig. 22: Plot graph of validation on PatchTST when perform forecasting on Snapchat time series data

PatchTST once again demonstrates a different approach, predicting an upward trend in the dataset. By splitting the data into smaller patches for deep learning, it effectively captures local patterns and nuances. This method allows it to detect the impact of recent changes more precisely. Based on its learning, PatchTST predicts that the sudden change in ratings will likely result in an upward recovery, as it aligns with Messenger's historical tendency to rebound and improve following a drop.

F. Model Evaluation

Model	App	MAE	RSE	MRSE
Autoformer	Snapchat	1.266	1.524	1.266
	Messenger	0.555	0.652	0.555
PatchTST	Snapchat	1.208	1.435	1.208
	Messenger	0.538	0.662	0.538

TABLE VII: Model Evaluation Metrics for Autoformer and PatchTST

Both the Autoformer and PatchTST models show better performance on Messenger compared to Snapchat, as indicated by lower MAE, RSE, and MRSE values. This suggests that the data from Messenger is generally easier to predict, possibly due to its more consistent patterns and lower variability. In contrast, Snapchat's data appears to be more complex, likely with higher fluctuations or less predictable trends, which makes forecasting more challenging.

PatchTST outperforms Autoformer in both datasets, demonstrating its superior ability to capture and predict temporal patterns. For Snapchat, PatchTST achieves lower error values across all metrics, indicating it is better at recognizing and forecasting the intricate temporal dynamics of the data. On Messenger, while PatchTST still performs better, the differences between the two models are smaller, suggesting that the data's relatively simpler structure makes both models perform well, though PatchTST maintains an edge. This consistency highlights PatchTST's robustness, as it performs effectively in both complex and more straightforward datasets.

Although Autoformer provides acceptable results, it exhibits higher error rates, indicating that it struggles more with the variability in Snapchat data and the finer temporal details in Messenger data when compared to PatchTST. The model's relatively weaker performance suggests it may not capture temporal patterns as effectively, particularly when the data is more volatile or requires finer temporal precision.

V. Conclusions and Recommendations

A. Snapchat

Conclusions

Snapchat's journey in Vietnam highlights both the potential and the pitfalls of operating in a culturally and politically nuanced market. The platform's strengths in localized engagement and innovation were evident in its creative use of augmented reality (AR) and features tailored to Vietnamese users. Snapchat's appeal to the younger demographic (18–34) and its celebration of cultural events like Tet strengthened its presence. However, the Hoang Sa and Truong Sa map controversy and the mishandling of Zenly's termination exposed vulnerabilities in cultural sensitivity and user transition strategies. These incidents disrupted its momentum but also demonstrated Snapchat's ability to recover through feature improvements and active user engagement.

Recommendations

1) **Enhance Geopolitical Awareness:** Incorporate a review process for global decisions to ensure alignment with local cultural and political contexts. For Vietnam, avoiding sensitive topics like national sovereignty is crucial to maintaining user trust.
2) **Develop Transparent Integration Plans:** For future acquisitions, communicate clear timelines and benefits to users. Ensure that features from acquired platforms, like Zenly, are smoothly integrated to retain user satisfaction.
3) **Invest in Crisis Management:** Build a robust crisis response team capable of addressing controversies promptly. Proactive communication can mitigate backlash and prevent prolonged damage to the platform's reputation.
4) **Capitalize on AR Innovation:** Expand AR capabilities by creating more localized and interactive features that resonate with Vietnamese users, particularly for cultural celebrations and trending events.
5) **Strengthen Youth Engagement:** Maintain a focus on privacy and playful design to align with the preferences of younger users. Explore partnerships with Vietnamese influencers to deepen connections with this demographic.

B. Messenger

Conclusions

Messenger's missteps in content moderation and public relations during the controversy over offensive GIFs of Ho Chi Minh underscored the platform's challenges in understanding and respecting Vietnam's cultural sensitivities. While the app made attempts at recovery, its efforts were overshadowed by increasing competition from Zalo, which has effectively addressed local needs through government integration, high file-sharing capacity, and a focus on community initiatives. Furthermore, global privacy concerns surrounding Facebook's parent company eroded trust, further limiting Messenger's recovery in Vietnam.

Recommendations

1) **Prioritize Content Moderation:** Implement stricter controls and partnerships with culturally aware moderation teams to ensure offensive or disrespectful content is promptly identified and removed.
2) **Foster Community Engagement:** Proactively address user concerns through transparent communication channels and initiatives that reflect cultural respect. Collaborate with local organizations to rebuild trust.
3) **Differentiate with Value-Added Features:** Introduce localized features such as integration with government services, improved file transfer capabilities, and community-focused tools similar to Zalo Connect.
4) **Enhance Privacy Features:** Counter global privacy concerns by adopting transparent data handling policies and promoting end-to-end encryption as a key feature for Vietnamese users.
5) **Reinforce Brand Positioning:** Launch targeted campaigns emphasizing Messenger's strengths, such as its extensive global connectivity, while addressing localized needs to regain market share.

Overall Outlook

Both Snapchat and Messenger in Vietnam demonstrate the importance of adapting to local contexts and addressing user concerns effectively. While Snapchat showed resilience in recovering from missteps, Messenger faces a steeper challenge in regaining user trust amidst strong competition from Zalo. For both platforms, prioritizing cultural sensitivity, localization, and user trust will be essential for long-term success in the Vietnamese market.

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