Understanding Feature Fatigue in Digital Platforms

A Review-Based Case Study on Zerodha Kite

Domain: Data Science | Text Analytics | Time-Series Analysis

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Introduction

Digital platforms regularly introduce new features to improve functionality and user satisfaction. However, over time, frequent additions and changes can also increase complexity and user effort. This case study explores how users respond to such changes by analyzing public feedback shared on the Google Play Store for the Zerodha Kite application. The goal of this study is not to evaluate product decisions, but to understand how user attention and sentiment evolve as different aspects of the application are discussed over time.

Using publicly available app reviews, this analysis groups user feedback into broad discussion themes such as feature requests, interaction complexity, support-related experiences, and overall satisfaction. By tracking how frequently these themes appear each month and how user sentiment changes alongside them, the study aims to identify patterns that may indicate increasing user effort or sustained attention toward specific areas of the application.

To summarize these patterns, a composite metric called the **Feature Fatigue Index (FFI)** is introduced. The FFI combines two observable signals from user reviews: how rapidly discussion around a topic grows and how sentiment behaves during that period. Topics that attract consistently high attention while showing softer sentiment trends are highlighted as areas that may benefit from closer observation. Overall, this case study demonstrates how large volumes of public user feedback can be transformed into meaningful, high-level insights that help understand evolving user experience patterns over time.

Problem Context

Modern digital applications evolve continuously, often introducing new features, updates, and improvements to meet changing user needs. While these updates are essential for growth and competitiveness, they can also increase the amount of information and effort required from users over time. Understanding how users react to this evolving complexity is important, especially for platforms with large and active user bases where small experience changes can affect a wide audience.

The challenge addressed in this case study is that user feedback is usually available in large volumes but remains underutilized for understanding long-term experience patterns. Individual reviews may highlight specific issues or praises, but they do not easily reveal broader trends such as whether certain topics consistently demand attention or whether sentiment shifts as discussion around those topics increases. This project attempts to bridge that gap by analyzing public review data over time to observe how user attention and sentiment align, with the aim of identifying recurring patterns that signal sustained user effort or growing interaction complexity.

Data Overview

To analyze how user discussions and sentiment evolve over time, this study required **time-stamped textual feedback** that reflects real user experiences at scale. Such data is well suited for identifying recurring discussion themes, measuring changes in user attention, and tracking sentiment patterns across different time periods. The focus was on obtaining structured feedback that captures both the content of user opinions and when those opinions were expressed.

The dataset used in this analysis consists of **1,000+ publicly available user reviews** collected from the **Google Play Store** for the Zerodha Kite mobile application. Each review record includes free-text feedback, a numerical rating, and a review date. The data spans multiple recent months, enabling analysis at a **monthly granularity** and supporting time-series comparisons across different discussion themes.

After collection, the raw review data was cleaned and prepared for analysis. This included removing duplicates, handling missing values, normalizing text (such as lowercasing and removing non-informative characters), and standardizing date formats. The processed dataset was then structured to support topic-based grouping, sentiment scoring, and time-series aggregation. This prepared dataset served as the foundation for all subsequent analyses, including topic discovery, sentiment trend analysis, topic velocity measurement, and the construction of the Feature Fatigue Index.

Topic Discovery from User Reviews

To identify recurring discussion patterns within user feedback, the review text was analyzed using **topic modeling techniques** commonly applied in natural language processing. Since raw text cannot be directly processed by statistical models, the reviews were first converted into a numerical representation using a **TF-IDF (Term Frequency–Inverse Document Frequency) vectorizer**. This approach emphasizes terms that are important within individual reviews while reducing the influence of commonly occurring words across the dataset.

The vectorized review data was then analyzed using **Latent Dirichlet Allocation (LDA)**, a probabilistic topic modeling method that identifies latent themes based on word co-occurrence patterns. LDA was applied to extract a fixed number of dominant topics, with each review assigned to the topic for which it had the highest probability. The number of topics was selected to balance interpretability and coverage, resulting in **six distinct discussion themes** that captured the majority of recurring feedback without excessive overlap.

Interpreted Topic Labels

Topic ID	Topic Label
Topic 0	Feature Requests & Interaction Complexity
Topic 1	Core Usage & Performance
Topic 2	Customer Support Experience
Topic 3	Interface Behaviour & Updates
Topic 4	Platform Reliability & Trust
Topic 5	General Feedback & Minor Issues

Table 1: Topic Distribution

The extracted topics were reviewed using representative samples of associated reviews and assigned descriptive labels for interpretability. These labels represent **high-level summaries of user discussion patterns rather than explicit feature classifications**. This topic-level structure forms the analytical foundation for subsequent time-series analysis, sentiment trend evaluation, and the computation of the Feature Fatigue Index.

Topic Velocity Over Time

After identifying dominant discussion themes, the analysis focused on understanding **how user attention toward these topics changed over time**. To capture this, a metric referred to as *topic velocity* was used, representing the **relative share of reviews associated with each topic on a monthly basis**. This approach allows comparison across time periods while accounting for variations in overall review volume.

By aggregating reviews by month and dominant topic, it becomes possible to observe which themes consistently attract user attention, which gain momentum, and which gradually decline. Topic velocity serves as a key signal for identifying areas that remain top-of-mind for users over extended periods, forming an important foundation for subsequent sentiment analysis and the construction of the Feature Fatigue Index.

Sentiment Trends Across Topics

While topic velocity captures *what users are talking about*, sentiment analysis helps explain **how users feel about those topics over time**. To assess this, sentiment scores were computed for individual reviews and then aggregated at a monthly level for each identified topic. This makes it possible to track changes in overall tone—positive, neutral, or negative—associated with different areas of discussion.

Sentiment scoring was performed using a lexicon-based approach, enabling consistent measurement across a large volume of short text reviews. Monthly averages were calculated per topic to smooth short-term fluctuations and highlight broader sentiment trends. This temporal view allows identification of topics where increased attention is accompanied by improving sentiment, as well as cases where sustained discussion aligns with softening or stagnant sentiment levels.

By examining sentiment trends alongside topic velocity, the analysis distinguishes between topics that attract attention for positive reasons and those that may reflect growing friction or dissatisfaction. These sentiment patterns provide critical context for interpreting discussion intensity and directly support the construction of the Feature Fatigue Index in the next stage of the analysis.

Feature Fatigue Index (FFI)

To consolidate the patterns observed from topic velocity and sentiment trend analysis, a composite metric called the **Feature Fatigue Index (FFI)** was computed at the topic level. The objective of this index is to summarize how user attention and sentiment interact over time for different discussion themes. Rather than evaluating individual features, the FFI provides a comparative view of discussion areas where sustained attention coincides with relatively weaker sentiment trends.

The index combines two normalized components: **topic velocity**, representing the relative intensity of discussion around a topic, and **sentiment trend**, representing how the emotional tone of feedback changes over time. Both components were normalized to ensure comparability across topics before being combined into a single score. Higher FFI values indicate topics that attract disproportionately high attention relative to their sentiment trajectory, making them useful candidates for deeper qualitative review.

Topic Area	**Topic Velocity**	**Sentiment Trend**	**Feature Fatigue Index**
Feature Requests & Interface Overload	High	Slightly Negative	High
Core User Experience & Usability	Moderate	Mildly Negative	Moderate
Customer Support & Accessibility	Low	Negative	Low
General App Satisfaction	Very Low	Neutral	Very Low
Platform Reliability & Trust	Very Low	Slightly Negative	Very Low
Minor UI Feedback & Responsiveness	Low	Positive	Very Low

Table 2: Feature Fatigue Index (FFI) Scores

The table highlights clear variation across discussion themes in terms of attention and sentiment alignment. Topics related to **feature requests and interface complexity** show the highest Feature Fatigue Index values, reflecting sustained user attention alongside softer sentiment trends. In contrast, areas such as platform reliability, general satisfaction, and minor interface feedback exhibit low index values, indicating more stable or positively aligned discussion patterns. These results reinforce the role of the FFI as a **relative, topic-level signal** rather than an absolute measure of product quality.

Key Findings

Concentration of User Attention Across Topics

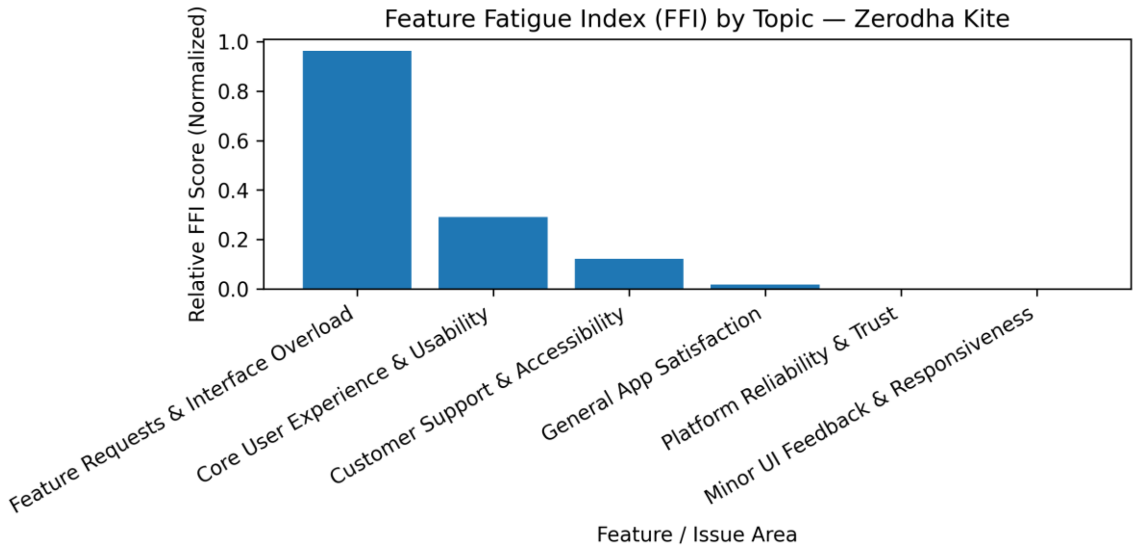

Figure 1: Feature Fatigue Index (FFI) by Topic

The Feature Fatigue Index (FFI) provides a single, comparable score to understand which issue areas demand the most user attention over time. As shown in Figure 1, *Feature Requests & Interface Overload* stands out sharply from all other topics, with a normalized FFI score close to **1.0**. In contrast, the next most prominent topic, *Core User Experience & Usability*, has an FFI score below **0.30**, while all remaining topics fall close to zero.

This large gap clearly shows that user feedback is **not evenly distributed** across topics. Instead, discussions are heavily concentrated around how features are introduced, structured, and managed within the application. Topics related to platform reliability, general satisfaction, or minor interface feedback contribute very little to overall fatigue when compared to this dominant area.

This tells us that users are not broadly unhappy with the platform. Rather, a single category of issues dominates attention, suggesting that complexity and feature accumulation are the primary sources of friction.

Relationship Between Attention and User Sentiment

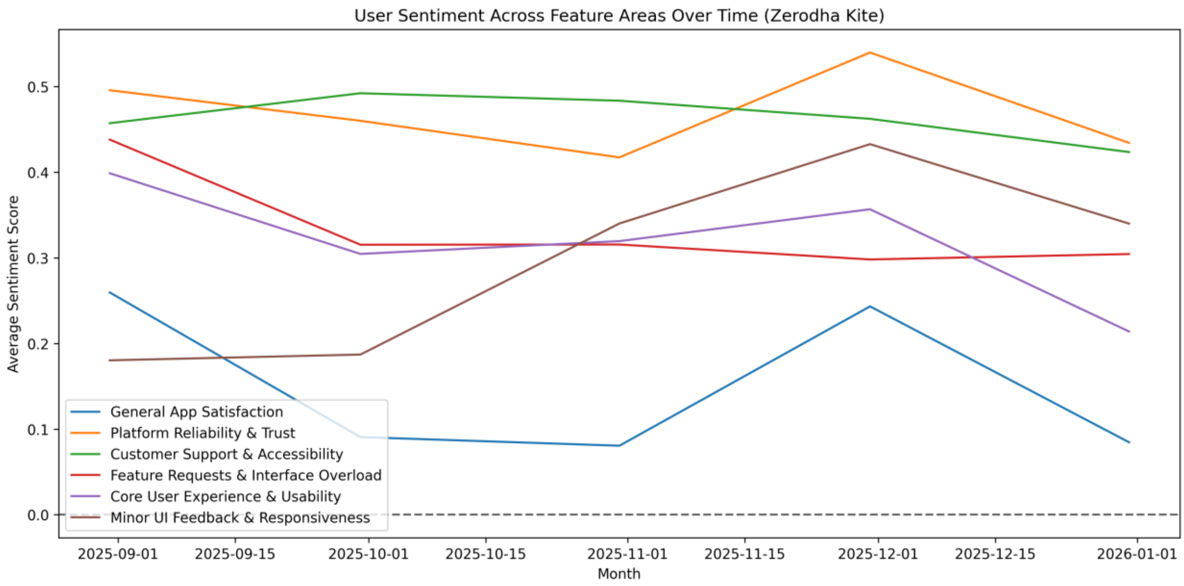

Figure 2: Sentiment Trends Across Topics Over Time

Figure 2 shows how average sentiment scores change over time for each topic. Topics such as *Customer Support & Accessibility* consistently maintain high sentiment values, staying in the range of **0.45 to 0.50** across most months. However, these topics attract relatively little discussion volume.

On the other hand, *Feature Requests & Interface Overload* shows consistently weaker sentiment. The sentiment score for this topic drops to around **0.08 in November 2025**, which is one of the lowest values observed across all topics and time periods. This decline occurs even as discussion around this topic increases significantly.

Here we can say users tend to write reviews more frequently when they experience difficulty or confusion rather than satisfaction. High attention combined with low sentiment strongly indicates unresolved pain points rather than neutral or positive engagement.

How User Attention Changes Over Time

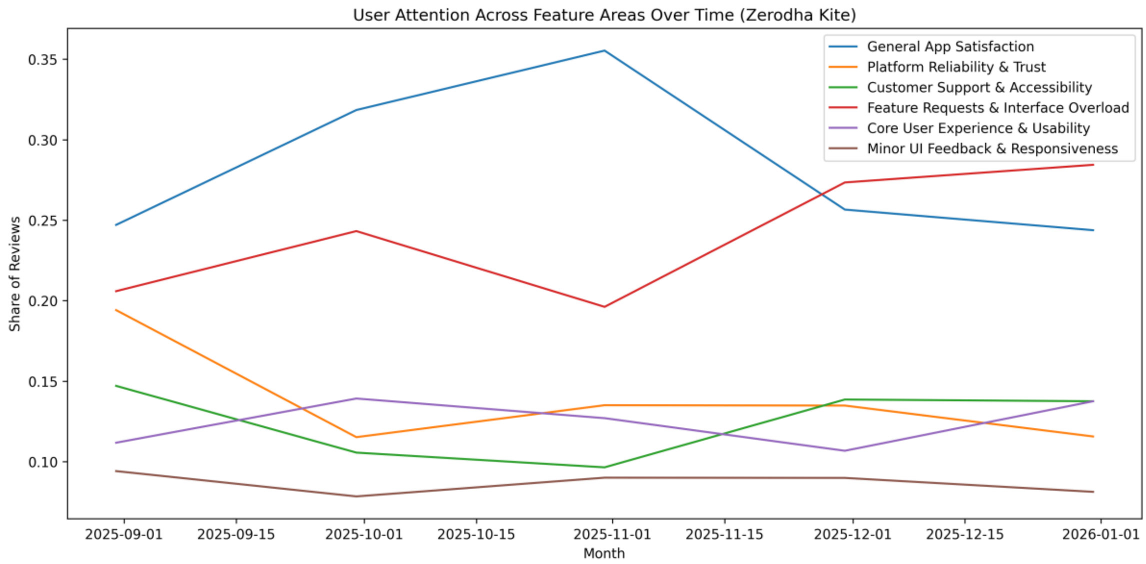

Figure 3: Topic Velocity Over Time

Figure 3 illustrates the share of reviews attributed to each topic on a monthly basis. *Feature Requests & Interface Overload* shows a steady rise from **September 2025 (~25%)** to a peak in **November 2025 (~35–36%)**, before declining slightly in the following months. During this same period, *Core User Experience & Usability* gradually increases and reaches approximately **29%** of all reviews by **January 2026**.

This pattern indicates that user attention does not vanish once an issue peaks. Instead, it shifts across closely related topics. When discussion around one issue area declines, another connected concern becomes more prominent.

This tells us that the user frustration appears to move through related problem areas rather than being resolved entirely. Attention cycles suggest ongoing friction rather than isolated complaints tied to a single moment.

A Small Number of Topics Drive Most User Friction

Across all three analyses—FFI, sentiment trends, and topic velocity—only **one to two topics (approximately 20%)** consistently show:

- High discussion volume
- Sustained presence across multiple months
- Lower or declining sentiment values

These topics account for a disproportionately large share of user feedback, while the remaining topics behave as background discussions with limited impact.

Therefore, focusing improvement efforts broadly across all areas is unlikely to be effective. The data clearly indicates that a small subset of issues drives most of the user friction and deserves prioritized attention.

Discussion

The findings suggest that as digital products grow in capability, user frustration often comes not from missing features, but from the effort required to understand and use what already exists. When new features accumulate without sufficient consolidation, users tend to focus their feedback on areas where the product feels mentally demanding rather than technically broken. For product teams, this highlights the importance of periodically slowing down feature expansion to evaluate how existing functionality fits together from a user's perspective.

The observed gap between discussion volume and sentiment also carries an important lesson. High engagement in reviews is not always a sign of success; in many cases, it reflects unresolved friction. Positive experiences tend to remain quiet, while confusing or demanding interactions repeatedly draw attention. This suggests that review data should not be read purely as feedback on quality, but as a signal of where users are investing the most cognitive effort. Identifying these areas early can help teams intervene before frustration becomes entrenched.

Finally, the shifting nature of attention across related topics indicates that user friction often moves rather than disappears. Addressing individual complaints in isolation may reduce noise temporarily, but underlying complexity can resurface elsewhere. A more sustainable approach involves grouping related features, simplifying workflows, and clearly communicating changes over time. For any growing digital platform, balancing innovation with clarity appears just as critical as introducing new capabilities.

Conclusion

This case study demonstrates how user-generated review data can be used to move beyond surface-level sentiment analysis and uncover deeper patterns of sustained attention and friction. By combining topic modeling, sentiment trends, and temporal analysis, the project shows that user dissatisfaction is often concentrated around a small number of recurring issue areas rather than spread evenly across a product.

The introduction of the Feature Fatigue Index (FFI) provides a practical way to identify these high-impact topics by jointly considering how frequently users discuss an issue and how sentiment evolves over time. This approach helps separate momentary noise from persistent signals, allowing attention to be focused on areas that consistently demand user effort. Importantly, the analysis highlights that high discussion volume alone is not sufficient; it is the combination of attention and sentiment that reveals meaningful patterns.

Overall, the findings suggest that as digital platforms mature, managing complexity becomes as important as adding new capabilities. The methodology presented in this study can be applied to other products and domains to better understand how users experience change over time and to support more informed, data-driven decisions around product evolution.