



Customer Retention in AI Tool Subscription Services: A Marketing Analytics Study of User Reviews

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Abstract. AI tool subscription services have become increasingly important in digital markets, yet customer retention remains a major challenge for providers. This study examines retention-related themes in AI tool subscription services from a marketing analytics perspective by analysing user review data from generative AI applications. Using two publicly available Kaggle datasets, the study applies rating-based sentiment classification, keyword-assisted thematic coding and frequency analysis to identify customer experience themes associated with satisfaction, dissatisfaction and potential retention risk. The primary dataset contains 7,736 reviews of five generative AI applications, and a supplementary ChatGPT dataset containing over one million reviews is used to validate the main findings. The results show that satisfaction and perceived value are the most frequent themes in user reviews, while price fairness, technical issues and retention-risk signals are more strongly associated with negative reviews. Trust / accuracy concerns show a different pattern, appearing more often in neutral reviews while remaining visible in negative reviews. These findings suggest that retention-related expressions in AI tool reviews are associated not only with technical capability, but also with perceived usefulness, pricing transparency, service reliability, trust and customer experience. The study contributes to digital marketing and consumer behaviour research by demonstrating how user review analytics can be used to identify retention-related themes in AI-enabled subscription services.

Keywords: AI tool subscription services, customer retention, marketing analytics, user reviews, perceived value, customer satisfaction, generative AI

1 Introduction

AI-enabled digital tools have become increasingly visible in everyday consumer and professional contexts. Generative AI applications, AI chatbots, writing assistants, productivity tools, coding assistants, image-generation tools and learning support tools are now used by a wide range of users to complete tasks, generate content, access information and improve efficiency. Many of these tools operate through subscription-based or freemium business models, where users may access basic features for free but are encouraged to pay for premium functions, higher usage limits, advanced models or improved service quality. In this context, AI tools are not only technological products;

they are also digital services that depend on user satisfaction, perceived value and long-term engagement [9, 16].

From a marketing perspective, the growth of AI tool services creates an important customer retention challenge. While many AI tools may initially attract users through novelty, curiosity or free trials, their long-term success depends on whether users continue to perceive sufficient value after the first stage of adoption. Subscription-based services are particularly vulnerable to customer switching because users can easily compare alternative tools, downgrade to free versions, cancel paid plans or stop using the service if expectations are not met. Therefore, retaining users requires more than technological capability. It also requires an understanding of how customers evaluate usefulness, trustworthiness, ease of use, pricing, privacy and overall satisfaction [4, 7, 9].

User reviews provide a valuable source of data for understanding these customer experiences. Unlike firm-generated marketing messages, user reviews reflect customers' own evaluations of their experiences with a product or service. Review texts and ratings can reveal what users appreciate, what they complain about, and what factors may influence satisfaction or dissatisfaction. In the context of AI tools, reviews may include comments about usefulness, accuracy, trust, usability, subscription cost, technical issues, privacy concerns and intentions to cancel or uninstall the app. As such, user reviews can be used as observable signals of customer experience and potential retention risk [6].

Although AI tools have attracted significant attention, much of the discussion focuses on technological development, adoption, productivity or ethical concerns. Less attention has been given to how user review data can be analysed from a marketing perspective to understand customer retention in AI tool subscription services. In particular, there is a need to examine how marketing-related factors such as perceived value, trust, usability, price fairness, privacy concerns and satisfaction appear in user-generated reviews, and how these factors may inform retention strategies for AI tool providers. Addressing this gap is important because AI tool providers compete not only through technical features, but also through customer experience, value communication and relationship management [1, 2, 11].

To address this gap, this study provides an empirical and contextual contribution by examining how established retention-related factors appear in user-generated review language within AI tool subscription services. It is guided by three research questions. First, what customer experience themes are most frequently reflected in user reviews of AI tool subscription services? Second, how do perceived value, trust, usability, price fairness, privacy concerns and satisfaction relate to positive and negative user sentiment? Third, how can user review analytics inform customer retention strategies for AI tool subscription providers?

2 Literature Review

Customer retention is a central concern in subscription-based digital services because business success depends not only on acquiring new users, but also on maintaining

continued engagement, renewal intention and customer loyalty. Compared with one-off purchase models, subscription services require customers to repeatedly evaluate whether the service remains useful, enjoyable and worth paying for. This is particularly important in freemium-based digital services, where users may begin with free access but only continue or upgrade when they perceive sufficient value from premium features. Prior research on freemium services suggests that perceived value is closely associated with users' intention to continue using a service and purchase premium content, highlighting the importance of value perception in digital subscription models [9, 14]. Perceived value generally refers to the user's overall evaluation of the benefits received compared with the costs involved, including money, time, effort and risk [17]. For AI tool subscription services, perceived value may include whether the tool saves time, improves productivity, supports learning or produces useful outputs, making it a relevant theme for examining retention-related review language when actual subscription renewal data is not available.

In addition to perceived value, trust, accuracy, privacy, usability and satisfaction are important for understanding continued use of AI-enabled services. Unlike many traditional digital tools, AI tools generate responses, recommendations or creative outputs that users may rely on for work, study, communication or decision-making. As a result, continued use depends not only on whether the tool is convenient, but also on whether users trust the quality and reliability of its outputs. Recent research on trust in AI emphasises that user trust is closely related to perceptions of system ability, reliability, safety, accuracy and robustness, particularly because AI systems can produce uncertain or incorrect outputs [2]. Privacy concern is also important because users may input personal or professional information into AI applications. Studies on conversational AI have highlighted the importance of privacy, security and trust perceptions in shaping user evaluations of AI systems [12]. Usability also matters because poor design or difficult onboarding may reduce satisfaction even when the tool has strong technical capability. In technology acceptance research, perceived ease of use and perceived usefulness are central factors shaping users' acceptance of information technology [7]. The expectation-confirmation model of information system continuance also suggests that satisfaction and perceived usefulness are important predictors of users' intention to continue using a system after initial adoption [4].

Online user reviews are valuable for marketing research because they provide direct, user-generated evidence of customer experience. They can reveal what customers value, what problems they encounter and what issues influence satisfaction or dissatisfaction, making them useful for exploratory marketing analytics. Prior research has shown that online reviews can influence consumer decision-making and market outcomes by affecting perceptions of product or service quality [6]. Marketing analytics involves using data to support marketing decision-making, customer understanding and service improvement. Recent research suggests that the use of marketing analytics can support customer agility and customer satisfaction by helping firms respond more effectively to customer information [1]. In the context of AI tool subscription services, user review analytics can help identify recurring customer concerns, detect dissatisfaction signals and inform exploratory retention strategy development.

3 Methodology

3.1 Research Design and Data Sources

This study adopts an exploratory marketing analytics design to examine customer retention in AI tool subscription services. The study does not aim to develop a machine learning prediction model or measure actual subscription churn. Instead, it uses user review data to identify customer experience themes that may be associated with satisfaction, dissatisfaction, continued use and potential retention risk. This approach is suitable because user reviews provide naturally occurring customer feedback and can reveal how users evaluate digital products and services in their own language, although they do not measure actual subscription renewal or cancellation behaviour [6].

This study uses two publicly available Kaggle datasets. The primary dataset is Gen AI apps user review from AppStore GooglePlay, which contains user reviews of generative AI applications from App Store and Google Play, including ChatGPT, BingAI, Microsoft Copilot, Gemini AI and DAVINCI [3]. This dataset was selected because it provides a cross-application view of user experiences in the generative AI tool market. It contains 7,736 English-language reviews associated with the United States, collected from 30 December 2023 to 24 March 2024. The key variables used in this study include app name, review description, rating, review date and platform source.

A supplementary ChatGPT review dataset is also used to strengthen the reliability of the analysis. The dataset, ChatGPT reviews [DAILY UPDATED], mainly contains daily updated user reviews and ratings for the ChatGPT Android application [10]. This supplementary dataset contains 1,020,141 ChatGPT reviews from 25 July 2023 to 2 May 2026. Because this dataset focuses only on ChatGPT, it serves as a supplementary validation dataset to check whether the main retention-related themes also appear in a much larger single-tool dataset.

3.2 Keyword-Assisted Coding Scheme

Data preprocessing was conducted before analysis. For the primary dataset, the review description column was used as the main text field because it contains users' written feedback. The rating column was used for sentiment classification, while the app name and source columns were used to compare review patterns across applications and platforms. The review text was converted to lowercase before keyword matching.

Reviews with four or five stars were classified as positive, three-star reviews as neutral, and one- or two-star reviews as negative. Keyword-assisted thematic coding was then used to identify customer experience themes in the review text. The coding scheme was developed based on the literature review and the key customer experience themes relevant to AI tool retention. Each theme represents a marketing-related factor that may be associated with retention-related expressions in AI tool reviews. As an exploratory single-researcher analysis, the coding focused on transparent keyword rules rather than inter-coder reliability testing. This approach is informed by thematic analysis, which is widely used to identify and report patterns within qualitative data [5]. Table 1 shows

the keyword-assisted coding scheme used to identify retention-related customer experience themes in the review text.

3.3 Data Analysis Procedure

The analysis followed five stages: dataset description, rating-based sentiment classification, keyword-assisted thematic coding, theme frequency calculation and retention-risk signal identification. The primary dataset was first summarised by app, platform and rating distribution. Reviews were then classified into positive, neutral and negative sentiment categories, and keywords were applied to identify customer experience themes, with each review allowed to contain more than one theme. Theme frequencies were calculated across the full dataset and compared by sentiment category. Retention-risk signals were identified through words and phrases related to cancellation, refund, uninstalling, switching or unwillingness to continue using the tool. The supplementary ChatGPT dataset was then used to check whether the same themes appeared in a larger single-tool dataset. Because the datasets do not include actual subscription renewal or cancellation records, the study identifies potential retention-risk signals rather than actual churn behaviour.

Table 1. Theme coding scheme

Theme	Definition	Example keywords
Perceived value	Whether users see the AI tool as useful, worthwhile or beneficial	useful, helpful, worth, valuable, saves time, productive
Trust / accuracy	Whether users trust the reliability and correctness of AI outputs	accurate, reliable, correct, wrong, inaccurate, misleading, hallucination
Usability	Whether the tool is easy and convenient to use	easy, simple, convenient, interface, difficult, confusing, hard to use
Price fairness	Whether users see subscription cost or paid features as reasonable	price, expensive, subscription, paid, pay, premium, trial, refund
Privacy concern	Whether users express concern about data, privacy or security	privacy, data, security, permission, safe, unsafe
Technical issues	Whether users experience bugs, errors or performance problems	bug, error, crash, slow, freeze, loading, login
Satisfaction	Whether users express overall positive or negative evaluation	love, great, excellent, bad, terrible, disappointed
Retention-risk signals	Whether users suggest possible cancellation, switching or discontinuance	cancel, refund, uninstall, delete, stop using, not renew, switch

4 Results

4.1 Dataset and Sentiment Overview

The primary dataset contained 7,736 user reviews of five generative AI applications collected from App Store and Google Play: ChatGPT, Copilot, BingAI, DAVINCI and Gemini [3]. As shown in Table 2, ChatGPT accounted for the largest proportion of reviews.

Table 2. App distribution in the primary dataset

App name	Number of reviews	Percentage
ChatGPT	3,488	45.09%
Copilot	1,862	24.07%
BingAI	1,115	14.41%
DAVINCI	681	8.80%
Gemini	590	7.63%
Total	7,736	100.00%

The reviews were relatively balanced across platforms, with 3,958 reviews from Google Play and 3,778 reviews from App Store. Ratings were classified into positive, neutral and negative categories. As shown in Table 3, the dataset was generally positive, while still containing enough negative reviews to examine dissatisfaction and review-based retention-risk signals.

Table 3. Rating-based sentiment distribution in the primary dataset

Sentiment category	Rating score	Number of reviews	Percentage
Positive	4-5 stars	5,608	72.49%
Neutral	3 stars	473	6.11%
Negative	1-2 stars	1,655	21.39%
Total	--	7,736	100.00%

Table 4 shows clear differences in sentiment across the five AI applications, suggesting that customer satisfaction and potential retention risk vary across AI tools.

Table 4. App-level rating and sentiment comparison

App name	Reviews	Average rating	Positive %	Negative %
ChatGPT	3,488	4.27	81.02%	13.90%
Copilot	1,862	4.10	76.26%	17.19%
BingAI	1,115	3.92	70.67%	22.24%
DAVINCI	681	3.17	50.81%	42.29%
Gemini	590	2.72	38.64%	53.22%

4.2 Theme Frequency and Sentiment Comparison

Keyword-assisted thematic coding was used to identify customer experience themes in the review text. Table 5 presents the frequency of each theme across the primary dataset.

Table 5. Theme frequency in the primary dataset

Theme	Reviews containing theme	Percentage of all reviews
Satisfaction	2,474	31.98%
Perceived value	1,337	17.28%
Technical issues	498	6.44%
Price fairness	482	6.23%
Usability	358	4.63%
Trust / accuracy	316	4.08%
Retention-risk signals	161	2.08%
Privacy concern	89	1.15%

Satisfaction and perceived value were the most frequent themes, while technical issues, price fairness, trust / accuracy and retention-risk signals appeared less frequently but remained important review-based indicators of dissatisfaction.

To better understand how customer experience themes relate to satisfaction and dissatisfaction, the study compared theme frequency across positive, neutral and negative reviews. Figure 1 presents the percentage of reviews within each sentiment category that contained each theme.

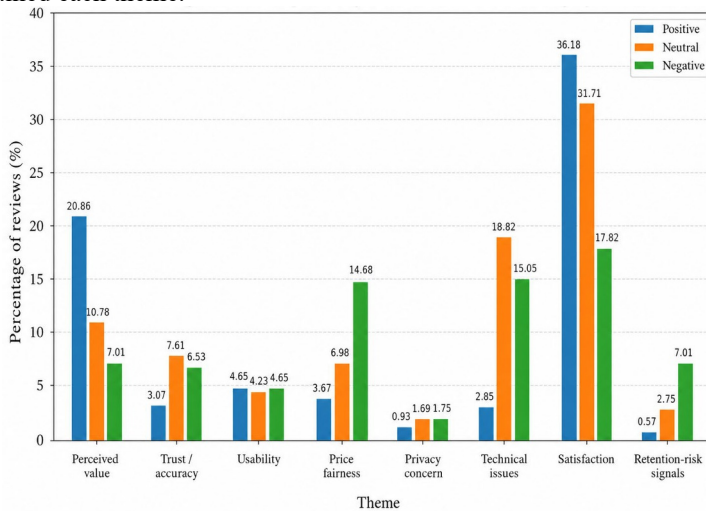


Fig. 1. Theme percentage within each sentiment category

As shown in Figure 1, perceived value was more common in positive reviews, while price fairness, technical issues and retention-risk signals were more visible in negative reviews. Trust / accuracy appeared more often in neutral reviews, suggesting a different

pattern. This indicates that usefulness supports favourable sentiment, whereas pricing concerns, technical reliability and discontinuance language are important warning signs in review-based retention analysis.

4.3 Supplementary ChatGPT Validation

The supplementary ChatGPT dataset was used to check whether the major themes identified in the primary dataset also appeared in a larger single-tool dataset. This dataset contained 1,020,141 ChatGPT reviews from 25 July 2023 to 2 May 2026 [10]. The supplementary dataset was highly positive overall, with 87.29% of reviews classified as positive. It also confirmed the main pattern observed in the primary dataset, as satisfaction and perceived value were again the two most frequent themes. Table 6 presents the supplementary ChatGPT validation results and shows that satisfaction and perceived value remained the most frequent themes in the larger single-tool dataset.

Table 6. Supplementary ChatGPT validation results

Measure	Result
Total reviews	1,020,141
Positive reviews	890,501 (87.29%)
Neutral reviews	42,604 (4.18%)
Negative reviews	87,036 (8.53%)
Satisfaction theme	390,125 (38.24%)
Perceived value theme	198,628 (19.47%)
Technical issues theme	21,826 (2.14%)
Price fairness theme	17,384 (1.70%)
Trust / accuracy theme	17,243 (1.69%)
Usability theme	17,234 (1.69%)
Retention-risk signals	3,459 (0.34%)
Privacy concern theme	3,304 (0.32%)

5 Discussion

5.1 Theoretical Findings

The findings suggest that perceived value and satisfaction are central to retention-related review language in AI tool subscription services because subscription-based tools require users to repeatedly evaluate whether the service remains worth using or paying for. Prior research suggests that users evaluate value by comparing the benefits received with the costs involved, including money, time and effort [17]. In freemium and subscription-based services, perceived value is also closely associated with continued use and premium purchase intention [9, 14]. Satisfaction is also closely related to whether the tool consistently meets user expectations and may influence users' willingness to pay for AI subscriptions [13]. The expectation-confirmation model of information sys-

tem continuance suggests that satisfaction and perceived usefulness are important predictors of users' intention to continue using a system after initial adoption [4]. Notably, perceived value still appeared in a small proportion of negative reviews, suggesting that some users may recognise the usefulness of AI tools while remaining dissatisfied with other factors such as pricing or technical reliability.

The results also show that price fairness and technical issues are important dissatisfaction triggers in user reviews. Pricing concerns are particularly relevant because many AI apps operate under freemium or premium-access models, where users may later encounter restrictions, paywalls or upgrade prompts. Research on consumer technology use suggests that price value can influence technology acceptance and use in consumer contexts [16]. Technical issues also directly affect customer satisfaction in digital services. Even if users value the idea of an AI tool, poor technical performance can reduce their willingness to continue using it.

Trust and accuracy are also relevant to AI tool retention, but they should be interpreted more cautiously than price fairness or technical issues, as recent research suggests that satisfaction, trust and perceived ease of use can shape continued usage intention in AI chatbot contexts [8]. In Figure 1, trust / accuracy appeared in both neutral and negative reviews at relatively similar levels, suggesting that these concerns are not as strongly negative-dominant as pricing or technical problems. This may be because users sometimes mention accuracy in a neutral or evaluative way, or because they may tolerate some inaccuracy when the tool is still perceived as useful. However, trust and accuracy remain important, particularly for professional, educational or high-stakes use cases where users rely on AI-generated outputs for work, study and content creation. Recent research on trust in AI shows that trust is closely connected to users' perceptions of system ability, reliability, safety, accuracy and robustness [2]. Privacy and security perceptions also matter in conversational AI because they shape users' trust and evaluation of AI systems [12]. In addition, retention-risk signals such as cancellation, refund, uninstalling or switching should be interpreted carefully. The dataset does not include actual subscription records, so these signals cannot be interpreted as evidence of actual churn. However, they remain valuable because they capture stated dissatisfaction in users' own words and may support early intervention [6].

Overall, review-based retention analysis in AI tool subscription services suggests a combination of positive value drivers and negative dissatisfaction triggers: perceived value and satisfaction support favourable sentiment, while price concerns, technical issues and retention-risk signals are more closely associated with dissatisfaction. Trust / accuracy concerns show a more neutral-to-negative pattern, suggesting that reliability issues remain important but should be interpreted more cautiously.

5.2 Marketing Implications

First, AI tool providers should communicate value through specific use cases rather than broad claims such as "powered by AI". Marketing messages and onboarding could A/B test task-based messages, such as writing support, study assistance, coding help or productivity improvement, to examine whether clearer value communication improves engagement.

Second, pricing strategy should be closely connected to perceived value. Providers should clearly explain what users receive from paid plans compared with free versions, as unclear premium features may make subscriptions appear unfair or not worth paying for. Transparent pricing pages, clear feature comparisons, simple cancellation or refund policies and flexible pricing options, such as student plans or low-cost entry plans, can reduce frustration and should be tested against user engagement and conversion outcomes.

Third, AI tool providers should improve technical reliability and build trust, because trust and perceived risk are increasingly recognised as important factors in AI-enabled service continuance [15]. Bugs, crashes, loading problems, login issues and inaccurate outputs can weaken user experience and reduce satisfaction, so providers should monitor reviews to identify recurring technical complaints and prioritise issues affecting access, performance or output quality. They should also build trust through transparent communication about what the tool can and cannot do, where users should verify outputs, and how the tool handles uncertainty, particularly for professional or high-stakes use cases.

Finally, AI tool providers should use review analytics for proactive retention and segmentation. Providers should monitor words related to cancellation, refund, uninstalling, switching or stopping use as early warning signs of potential churn. Although review data cannot directly measure actual subscription cancellation, it can help providers identify dissatisfaction before it becomes more widespread, while marketing analytics can support customer understanding and service improvement [1]. Reviews can also support segmentation because students may be more price-sensitive and value learning support, while professionals may prioritise accuracy, reliability and workflow integration; these segment-level assumptions should be validated through surveys or usage data. Overall, retention should be built into the whole customer experience rather than treated as a one-time conversion goal.

6 Conclusion

This study examined customer retention in AI tool subscription services from a marketing analytics perspective by analysing how customer experience themes such as perceived value, satisfaction, price fairness, technical issues, trust / accuracy, privacy concern and retention-risk signals appeared in user reviews. It adopted an exploratory review-based approach rather than a machine learning prediction model to identify marketing-relevant patterns that can support customer retention strategies in AI-enabled digital services.

The findings show that user reviews of AI tools were generally positive, with satisfaction and perceived value emerging as the most frequent themes across both datasets. Price fairness, technical issues and retention-risk signals were more strongly associated with negative reviews, while trust / accuracy appeared more often in neutral reviews and remained visible in negative reviews. This study contributes to digital marketing and consumer behaviour research by showing how established retention-related themes appear in AI tool subscription reviews when company-level churn data is unavailable.

Several limitations should be acknowledged. First, the study used publicly available reviews rather than company-level subscription records, so retention-risk signals should be interpreted as stated discontinuance expressions rather than evidence of actual churn. The relationship between these review-based signals and actual subscription cancellation remains unknown and should be tested with behavioural data. Second, online reviews may overrepresent users with very positive or very negative experiences, potentially overstating pricing complaints or technical frustrations while underrepresenting silent churners. Third, the primary dataset was limited to English-language reviews associated with the United States and covered a relatively short period, while the supplementary dataset focused on one AI tool. Finally, keyword-assisted coding may miss indirect language, slang or sarcasm, and the absence of demographic, usage and subscription plan variables limited the ability to compare user segments.

Future research could extend this study by using survey data or company-level subscription and usage data to directly examine continued subscription intention, renewal, cancellation and churn behaviour. Future studies could also apply more advanced text analytics or machine learning methods to larger review datasets, such as topic modelling, sentiment analysis or supervised classification, and compare their results with theory-driven keyword coding. Finally, researchers could compare different categories of AI tools and user segments, such as students, professionals, educators, creators and business users.

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