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Customer Perception Analysis of Netflix Through Aspect-Based Sentiment and Emotion Analysis Using Natural Language Processing (NLP)

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Abstract : The high growth in the number of OTT streaming services means there is now more competition and thus it is increasingly important to measure how customers perceive these services in order to be able to improve service quality and customer loyalty. This research investigates how customers perceive the Netflix app in India. A total of 5000 real-time User Reviews were collected from the Google Play Store and then text analytics was performed on these reviews. Python was used to scrape the reviews and they were then analysed through a comprehensive Natural Language Processing (NLP) Framework. This process used VADER Sentiment Analysis, NRC Emotion Lexicon, Text Preprocessing and an Aspect-Based Sentiment Method focusing on five dimensions of Netflix, i.e., Content, Quality, Convenience, Features and Price. Sentiment Analysis results indicate that the reviews were fairly even, 47 % were Positive, 33 % Negative and 20 % Neutral. Emotion Analysis results indicate that the most expressed of emotions were Trust, Anticipation and Joy. The emotions that were frequently expressed, such as Fear, Sadness and Anger indicate the existence of a greater level of Concern or Frustration. According to aspect level analysis, customers showed a higher level of positive perceptions about the following aspects: content, quality and features; whereas customers' perceptions about Price were the greatest proportion of the negative or unhappy reviews, being more than fifty per cent. Convenience shows a mixed perception, with a considerable number of concerns regarding usability & App performance. This research contributes to the existing body of OTT literature by modelling consumer-generated reviews through an integrated analysis of sentiment, emotion, and aspect-based insights across large volumes of user reviews. The findings offer valuable guidance for OTT managers, enabling them to prioritise strategic improvements based on data-driven consumer perceptions.

***IndexTerms* - Sentiment Analysis, Emotion analysis, Natural Language Processing, VADER, NRCLex.**

I. INTRODUCTION

Recent trends show that the OTT video streaming industry is growing rapidly, thanks to the increasing use of smartphones and the growth of high-speed internet, as well as a cultural shift away from traditional television viewing towards digitally available entertainment that can be streamed anytime and anywhere. OTT Video Streamers have changed how people use and consume media, offering customised content options, the ability to view programs on multiple devices, and the option for no advertising during the viewing experience. For OTT streaming providers to successfully compete in this increasingly crowded market, understanding how customers perceive their products, influences their satisfaction level, influences their decisions when deciding whether to purchase a subscription, loyalty to the platform, and continued revenue growth in the long run is becoming an important area of focus for OTT providers. Netflix is one of the most prominent OTT streaming providers that has successfully gained a foothold in India with localised programming, a large selection of content, and robust digital marketing initiatives (Farooqui, 2025). Nevertheless, the Indian market has a unique behavioural profile with a substantially greater price sensitivity than most other OTT video streaming markets, highly variable regional programming interests across India's vast geographic spread, and increased competition from multiple OTT platforms i.e. Amazon Prime Video, Hotstar, SonyLiv, and regional OTT providers. In this competitive landscape, the feedback that customers provide about their OTT streaming experience via Digital Channels, especially as captured in user reviews on an App Store, can be a very useful and valuable representation of how users are experiencing the OTT service i.e. how well their expectations were met or exceeded and how much dissatisfaction they had with the OTT service and experience. The information that is provided by the users in their Google Play Store app reviews can provide a unique and valuable perspective on how subscribers of OTT streaming services perceive and judge OTT content quality, pricing, usability, streaming experiences, and specific features of the OTT Service offering.

The current research was inspired by the above gaps in the existing literature regarding customer perception of Netflix in India, and adopts an integrated analytical framework that integrates both sentiment analysis and emotional extraction techniques, as well as aspect-based sentiment analysis, using 5,000 Google Play Store app reviews to analyse customer sentiment toward Netflix. This research aims to identify the overall customer sentiment regarding Netflix and provide an overview of emotional expressions and perceptions related to Netflix, specifically for five service dimensions: Content, Quality, Convenience, Features, and Price. The analysis will be performed using Python-based NLP methodologies to provide actionable insights that will assist Netflix in optimising the platform, creating new services and products, and developing a competitive strategy within the Indian marketplace.

II. Statement of the Problem

Most previous OTT platform-related studies regarding the Indian market (Samala N, 2024, Soren AA, 2024) have relied on structured survey methodology, which has focused primarily on either adoption intention or satisfaction from using OTT services, and little insight has been provided regarding the users' emotional response and experiential feedback received while using services on the OTT platform in real-time. Very few comprehensive studies had used the actual user-generated review data (Gnanapriya and Gopikrishna, 2025) in order to examine customers' sentiment and what specific aspects of the services have impacted customers' perceptions through the application of advanced Natural Language Processing techniques. There hasn't yet been any research that has included the integration of sentiment analysis, emotion mining, and aspect-based sentiment analysis of customer perception of Netflix within India into one unified framework with data scraped off the internet.

The need to assess Indian consumers' perceptions of Netflix has never been more critical, particularly due to the limited empirical research examining Netflix's brand perception in the Indian market. While Shafira and Nugraha (2025) analysed Netflix app reviews using the Naïve Bayes algorithm in the Indonesian context, the present study extends this line of inquiry by focusing on India and adopting a more comprehensive analytical approach. Specifically, it employs text-based sentiment and emotion analysis techniques to examine customer perceptions of the Netflix platform. By analysing actual consumer comments obtained from large-scale, real-world survey data, this study evaluates user perceptions across key dimensions, including content, quality, convenience, features, and price. Addressing this research gap will provide deeper insights into the primary drivers of consumer experience and assist Netflix in formulating strategic initiatives to enhance service quality and sustain a competitive advantage in the Indian market.

III. Literature Review

3.1 OTT Platforms and Consumer Perception

Consumer perception is an important factor for users choosing to adopt an OTT service and impacts user perceptions of satisfaction, choice of OTT service provider, and likelihood of continuing subscription to an OTT service. The literature shows that the variety and quality of content offered by a service and the price charged for the service, as well as the perceived usefulness of the streaming service to consumers, significantly impact their perception of the service. Ali and Kumar (2021) demonstrated that Indian consumers' evaluation of OTT services is primarily based on the perceived entertainment value of the service, the availability of content and ease of accessing content. Similarly, Bhatt (2021) found that both the quality of the content offered and convenience to the consumer in using the service play a large part in determining the level of satisfaction a consumer experiences with an OTT service. Similarly, Yousaf et al. (2021) found in a multi-nation study that perceived value, reliability and emotional connection to an OTT service impact the consumer's intention to recommend that service to others. As such, OTT perception can be said to involve multiple dimensions characterised by functional (e.g., quality, usability) and emotional (e.g., enjoyment, trust) aspects.

3.2 Sentiment Analysis and NLP in Consumer Perception Research

A significant number of user generated reviews on platforms like the Google Play Store give us insight into customer experience using a qualitative perspective. Using Sentiment Analysis as a tool to extract emotional and attitude-related information from this type of text has been shown to be a powerful approach. A survey by Mewari et al (2015) discusses the value of computational tools in conducting Opinion Mining to enable extraction of user attitudes from large unstructured datasets. Hu and Liu (2004) established the groundwork for extracting sentiment. They introduced Feature-based Sentiment Analysis, which is based on an understanding of the various aspects of a particular review and assessing the amount of sentiment related to that review. Feature-based analysis is now a common approach to the analysis of consumer activity in the digital environment. VADER, which is derived from an acronym for Valence Aware Dictionary for Sentiment Reasoning, offers a lexicon as well as a rule-based approach to analyzing Short Social Media Posts. Hutto and Gilbert (2014) developed VADER which can be used to analyze App Reviews, Tweets, and other forms of Conversational Language based upon the company's belief that its mechanism for calculating compound scores will provide better results in a text-based environment. VADER is widely used because it is easy to use and provides highly accurate results. Using Emotion analysis provides a much richer understanding of individuals' responses to stimuli that are not limited to polarities only. The NRC Emotion Lexicon as compiled by Mohammad and Turney (2013) contains word-to-emotion mappings for 8 basic emotions, i.e. Joy, Trust, Fear, Surprise, Anger, Anticipation, Sadness, and Disgust. The NRC Emotion Lexicon is available to implement using the NRCLex interface (Bailey, 2022).

3.3 Text Analytics and Sentiment Studies on OTT Platforms

Although computational studies on OTT application reviews have been limited to date, there are some significant papers published. One such study, by Shafira and Nugraha (2025), provided a quantitative assessment of Netflix application reviews on the Google Play Store; they found that the majority of reviewers expressed discontent with Netflix due to its pricing policy, account limitations, and various technical issues. Although the methodology employed by the researchers involved merely a sentiment classification of the application review texts to form their results, their study highlights how important text analytics can be for better understanding why users are not satisfied.

In addition to academic research, various industry-level analyses further confirm the findings of the aforementioned studies. For example, AInvest (2025) states that Netflix invests heavily in regional content and tiered pricing to boost global revenue and usage, particularly with mobile-focused plans in emerging markets, confirming the continued relevance of both pricing and content strategies to users' perceptions.

Even though the existing literature has provided significant insight into user attitudes towards OTT services, research that applies integrated sentiment analysis, emotions mining, and ABSA techniques remains limited, particularly within the Indian market. Therefore, this creates a unique opportunity for researchers to investigate consumer perceptions within a multidimensional and more granular framework using advanced NLP methods.

IV. Objectives of the Study

The primary goals of this study, as defined by the literature analysed, include:

- Using Natural Language Processing techniques to analyse user-generated Netflix reviews and identify key service aspects (content quality, pricing, user experience and personalised recommendations) through user-generated Netflix reviews.
- Using aspect-based sentiment analysis to assess the polarity of customer opinions on Netflix's service aspect(s). This will be accomplished using the VADER software.
- Fine-grained emotion detection to understand the dominant emotions associated with customer feedback on Netflix (e.g., joy, trust, anger, anticipation). The NRCLex software will be used for this purpose.
- Interpret and visualise customer sentiment and emotional response ties to ascertain customers' overall perceptions of Netflix and provide recommendations on how to enhance the Netflix service experience.

V. Methodology of the Study

5.1 Research Design

To gain insight into customers' perception of the Netflix mobile application (in India,) this research uses a computational method of text analytics to analyse their reviews (posted) in real-time. To achieve this objective, the researchers implemented a multi-stage Natural Language Processing pipeline using the Python programming language for extracting, preprocessing, and analysing the Google Play Store reviews. The researchers utilised a combination of sentiment analysis, emotion mining, and aspect-based sentiment analysis (ABSA) as methods to determine how consumers evaluate different service dimensions of Netflix.

5.2 Data Source and Collection

The Google Play Store served as the source for collecting user-generated reviews because it is an excellent source of naturally occurring (real-life) customer experience data. In addition, researchers were able to programmatically extract these user-generated reviews and app metadata via the Google Play Scraper Package (using Python).

The raw dataset contained a total of 5,000 reviews; therefore, it was necessary for the researcher to systematically clean the dataset before performing any further analysis.

```
                               reviewId       userName  score  \
0  9f56d114-5d2c-40df-9885-35a35fc4be57  A Google user      5
1  b829072c-e92b-4f53-9837-39f4b63551eb  A Google user      1
2  1dac10a0-1f01-42e2-8cda-4228fc47a219  A Google user      3
3  560b9cf1-4b8f-4769-94d2-6d8531160101  A Google user      1
4  a835e95f-99f3-4d16-9a71-4cf10b5fd13d  A Google user      5

                   at                                            content
0 2025-10-20 19:42:02                                            awesome
1 2025-10-20 19:39:12  app sucks there's no reason for there to be a ...
2 2025-10-20 19:39:10  its a good app and friendly to use but there i...
3 2025-10-20 19:14:20    toooo much signup time ,,, and unable to signup
4 2025-10-20 19:12:38                                              great
```

Fig. 1: Sample of web scraped reviews

5.3 Data Cleaning and Preprocessing

Preparation of Reviews for Analysis through Text Preprocessing and Data Preparation: We utilised a standardised approach to text preprocessing to prepare the review data for analysis. Specifically, we have done the following:

- Removed URLs, HTML tags, numbers and emojis. We also used REGEX to remove additional noise from the text.
- All text was converted to lowercase to create uniformity.
- Stopwords were removed from the review texts. We were able to improve upon the meaningful words in each review by utilising NLTK's stopword catalogue.
- Words were lemmatised; this was done with the WordNet Lemmatizer to create a consistent word base.
- Length Filtering: Reviews which are less than three meaningful words were removed from the analysis. This allows us to calculate the sentiment/emotion scores based on genuine reviews.

After processing the reviews, the reviews were compiled into a consolidated dataset with the meaningful review text ready for analysis.

	cleaned_text	compound	Sentiment
1	app suck there reason household one wanted rui...	-0.9610	Negative
2	good app friendly use tamil language movie tam...	0.7269	Positive
3	toooo much signup time unable signup	0.0000	Neutral
5	please input filipino subtitle anime like boru...	0.7430	Positive
7	bad customer care service making successful pa...	0.5423	Positive
8	e la mejor	0.0000	Neutral
9	like really fun watch story	0.7264	Positive
11	google pixel pro update summer volume severely...	-0.7506	Negative
12	subscribtion hardi paid time unable watch cust...	0.0000	Neutral
13	great selectiongreat app	0.6249	Positive

Fig. 2: Cleaned Reviews

5.4 Sentiment Analysis

Sentiment Analysis was conducted using VADER (Valence Aware Dictionary and sEntiment Reasoner) developed by Hutto and Gilbert (2014). VADER was chosen because it is optimised for evaluating social media and app reviews based on the following: Informal Language Capitalisation, Emojis Exclamatory and Emphasis Slang and/or abbreviation. Why VADER was Chosen: Provides accurate scores for user-generated, short-form content, provides polarity probability and compound sentiment score, heavily Utilised and Widely Studied through Academia Implementation. For each review, VADER outputs four separate scores: Positive, Negative, Neutral and Compound Sentiment Score. The sentiment polarity for each review will be classified as follows: Positive → Compound Score ≥ 0.05, Negative → Compound Score ≤ -0.05, Neutral: otherwise.

5.5 Emotion Analysis

In addition to detecting polarity, the NRC Emotion Lexicon, developed by Mohammad & Turney (2013) and accessed through the NRCLex Python library (Bailey, 2022), was used to acquire the emotional tone of a piece of text. The following eight primary emotions were detected from the emotional tone data: Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise and Trust. For every review, words in the review were matched with the respective NRC emotion categories. The emotional frequency of each review was then calculated. The total number of emotions was then added together over time to create one overall number for each of these emotions. The dominant emotions were Trust (highest), Anticipation and Joy. Moderately, there were negative emotions, such as fear, sadness, anger, and disgust, showing some level of frustration for the users involved.

5.6 Aspect-Based Sentiment Analysis (ABSA)

Aspect-based sentiment analysis (ABSA) was performed to gather knowledge on customer's perception of specific service aspects of Netflix. Aspects were created using a keyword-based rule extraction technique developed by Hu & Liu (2004), rather than through a machine-learning approach. Five aspects were analysed: Content, Quality, Convenience, Features and Price. A curated keyword list for each of the five aspects was established. aspects = { 'Content': ['movie', 'series', 'show', 'content', 'episode', 'story', 'film'], 'Quality': ['video', 'sound', 'resolution', 'quality', 'hd', 'clarity', 'stream'], 'Convenience': ['download', 'loading', 'buffer', 'app', 'subscription', 'login', 'interface'], 'Features': ['recommendation', 'feature', 'option', 'profile', 'search', 'subtitle', 'language'], 'Price': ['price', 'cost', 'plan', 'subscription', 'expensive', 'cheap', 'value'] }. Each review was searched for the keywords collected. Reviews could encompass more than one aspect. Sentiment scores were matched to each review of each of the five aspects.

VI. Results and Discussion

According to sentiment analysis on the reviews of Netflix, a majority of customers viewed Netflix positively; 46.81% of their reviews were positive while 33.11% were negative and 20.08% were neutral, as given in Figure 3. Therefore, the results of the survey show that almost 50% of customers are happy with their experience; however, there are still a number of unhappy customers who mentioned negative experiences. Negative sentiments are usually related to customers being unhappy about pricing, issues logging into their accounts, or being interrupted from watching the movie due to buffering or other reasons. The distribution graph shows a stark difference in the positive-to-negative ratio of the reviews and indicates that even though Netflix has an extremely good image as a company, there are still some issues connected with their service that have a direct impact on user experience.

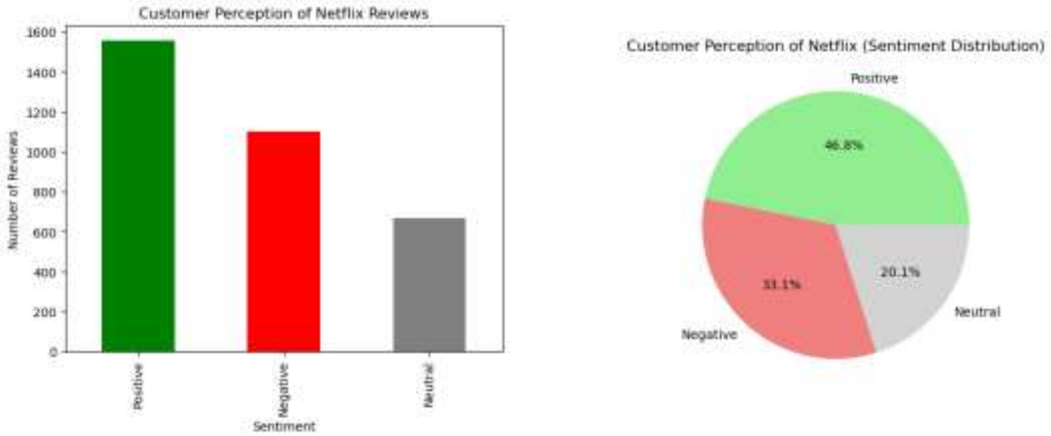

Fig. 3: Sentiment Distribution of Reviews

Information from the NRC Lexicon provided a deeper level of understanding into the customer's point of view and identified the emotions associated with the user reviews. The top three emotions that customers expressed were trust, with 3,059 instances, followed by anticipation (2,846 instances) and joy (2,040 instances) from Figure 4. These results illustrate that on the whole, customers have confidence in the service and are excited to see new content that will soon be on Netflix. There were other negative emotions (fear, sadness, anger and disgust) expressed by customers related mostly to account restrictions, technical problems, unexpected changes to their subscription plan and/or price increases. Therefore, the emotional structure of customers' reviews suggests that customers experience mixed feelings of enjoying the service but having ongoing frustrations, which is consistent with the buying habits of consumers when they choose one OTT (over-the-top) service over another.

Trust	3059
anticipation	2846
Joy	2040
Fear	1872
sadness	1535
Anger	1309
disgust	1045
surprise	972

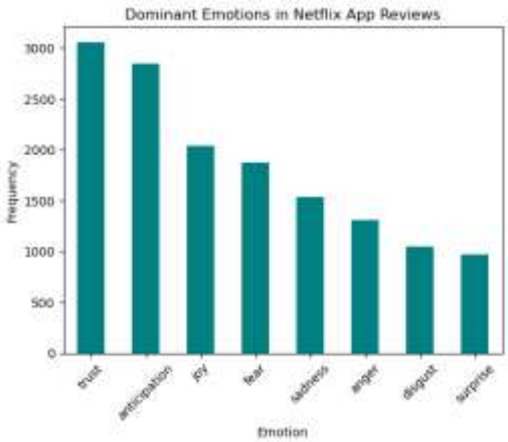

Fig. 4: Emotion Distribution of Reviews

Based on the results of the aspect-based sentiment analysis, it can be concluded that users are generally satisfied with Netflix's offerings relative to other streaming services, but have significant concerns about the pricing of Netflix subscriptions and the technical aspects of using a Netflix account. Users appreciate the wide variety, originality, and overall quality of shows and movies that are available to them through Netflix, as evidenced by 56.98% of content-related sentiments being rated positively. Similarly, quality and feature-related sentiments received high ratings for positive sentiment, indicating that users are pleased with how much clearer the videos are when watching on Netflix, as well as how well Netflix provides recommendations to them, along with the ease with which they can navigate through the interface. Although convenience-related sentiments had a more even distribution of positive and negative responses, because users expressed concern about the number of devices that can be used to access their Netflix account, as well as downloading issues and restrictions on sharing accounts with other people. On the other hand, price appeared to have the most negative effect on users, with 50.77% classified as such. Users expressed dissatisfaction with the continually rising cost of Netflix subscriptions, along with the limited number of affordable subscription options available to them and the overall perceived value of subscriptions received.

Fig. 5: Word Cloud of Most Frequent Words in Reviews

Table 1: Percentage Distribution of Aspects with respect to Sentiments

	Positive	Negative	Neutral
Content	56.97577	29.82456	13.19967
Quality	54.40415	38.8601	6.735751
Convenience	47.41185	38.4096	14.17855
Features	54.31655	30.21583	15.46763
Price	37.8866	50.7732	11.34021

In addition, with the aid of the heatmap analysis, it can be seen that strong positive sentiment clusters around content, quality and features, while concentrated clusters of negative sentiments surround the price of a Netflix subscription. Overall, these findings show that Netflix has a solid reputation for their content library and the overall quality of their platform; however, the current pricing model along with the limitations many subscribers experience with the technical aspects of accessing content, both have created issues for subscribers and, ultimately, need to be addressed by Netflix to improve user satisfaction and maintain their competitive stance within the industry.

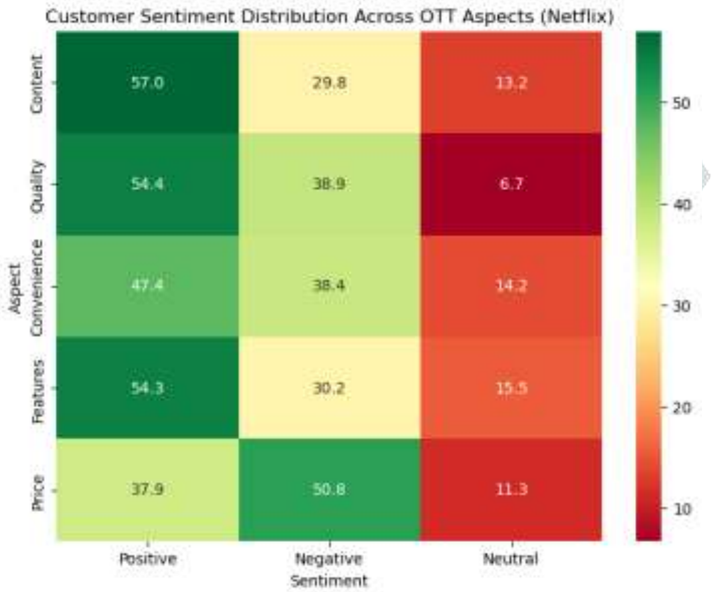

Fig. 6: Heatmap of Customer Sentiment Distribution across Aspects

VII. Conclusion

Using Google Play Store reviews, this study explored Netflix's mobile application through various methods of analysing customer reviews, including sentiment analysis, emotion detection and aspect-based opinion mining. Results indicate that patrons view Netflix favourably overall and are especially trusting, hopeful, and happy about the product. Quality content is the best indicator of users' positive attitudes towards Netflix; users have commented on the great variety, originality, and relevance of its shows. Users provided positive feedback on their experiences with streaming quality (how good the video was streamed) and features (the functionality of the app) and design (the layout of the app), confirming that Netflix does a great job of delivering both content and a good user experience.

There were also significant areas of dissatisfaction identified through this analysis. Price was seen as the most negative aspect of Netflix; the majority of comments associated with the price mentioned worry about rising subscription costs or a lack of affordable options. Another negative aspect mentioned was problems with technology, device limitations and account-sharing problems. Many users felt angry, frustrated, or sad when experiencing technical or operational problems with Netflix. This analysis indicates Netflix is performing strongly in terms of content and streaming quality, but there are aspects associated with Netflix's pricing and operations causing dissatisfaction among users.

The findings from this evaluation indicate that a consumer's opinion of Netflix is made up of many factors, including emotional responses and evaluation through experience. To remain competitive within an increasingly saturated OTT (over-the-top) environment, it is important that Netflix maintains content superiority while at the same time eliminating pricing concerns and functional discrepancies associated with differentiation and product quality. The analytical approach taken within this study has also demonstrated that online consumer feedback can offer an opportunity for companies to gather actionable information regarding how their customers perceive them as being successful or unsuccessful, therefore allowing companies to optimise their strategic planning and marketing strategies as they grow their business on digital platforms.

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