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Digital echoes of herbal healing: Sentiment analysis of Ashwagandha supplements reviews

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Abstract

E-commerce platforms provide useful information about consumer attitudes towards dietary supplements. This study examined stated consumer opinion by analysing 200 recent Amazon India reviews of Ashwagandha-based dietary supplements promoted for stress treatment. Textual data were processed and analyzed in R using the NRC framework for lexicon-based sentiment categorization, using an ex post facto research methodology. The reviews were divided into eleven emotional components, which included trust, joy, anticipation, fear, and sadness. Positive and trust-related sentiments were shown to be more common than negative emotions such as fear and disgust. A stratified study of star ratings and confirmed purchase status indicated significant disparities in emotional intensity, with lower-rated reviews more commonly citing worries about side effects and perceived ineffectiveness. Quantitative n-gram analysis revealed repeated terms such as "stress relief," "good quality," and "side effects," emphasizing functional evaluation as an important driver of consumer feedback. The findings reflect subjective consumer impressions rather than clinical efficacy. By combining sentiment distribution, subgroup comparison, and lexical pattern analysis, this study shows how organized evaluation of online reviews can guide product marketing strategies and promote responsible post-market monitoring in the dietary supplement industry.

Keywords: *Ashwagandha, dietary supplements, sentiment analysis, consumer perception, text mining, post-market monitoring*

Introduction:

Ashwagandha (*Withania somnifera* L. Dunal) is a robust medicinal herb that can survive in dry conditions (Saran, 2023). This crop grows on its own in dry to semi-dry phytogeographic areas that stretch from central to western Rajasthan. From both a health and an economic point of view, ashwagandha is incredibly essential because it has so many health benefits. If the right crop is grown at the right place, it will have a big effect on the availability of high-quality raw materials. This can guarantee the availability of ashwagandha root in the international market, ultimately boosting demand and providing a favourable financial return to the producers. (Kumar *et al.,* 2011). The herbal sector must prioritize building robust brands, employing effective agricultural and harvesting methods, and investing in research and development. (Singh, R. *et al.,* 2025). Many functional food formulations have used ashwagandha to enhance their health benefits. As the need for natural, non-pharmaceutical healthcare grows, so does the demand for plant-based supplements. Functional foods now make up a sizable portion of the global food market. This is due to the fact that they provide necessary nourishment and health benefits. Ashwagandha improves the standard formulations for immunity, anti-inflammatory effects, and cognitive wellness (Hussain *et al.,* 2015). The component of modern diets reflects the wellness industry's increased interest in natural therapeutic choices, particularly with relation to how people manage stress, improve their mental health, and improve their physical performance (Nowak *et al.,* 2023). In many nations, Ashwagandha is included in wellness programs aimed at stress reduction, mood enhancement, and mental clarity. More recently, Ashwagandha has been integrated into modern wellness trends such as herbalism, holistic health, and mindfulness techniques. In this context, Ashwagandha is regarded for its physical benefits, as well as an enhancer of mental and emotional balance (Rakha et al. 2023). It has become a popular option in the sports nutrition industry due to its increasing recognition for its capacity to control blood sugar, improve athletic performance, and aid in muscle recovery. The primary components of ashwagandha's adaptogenic qualities are its bioactive chemicals, which have demonstrated encouraging outcomes in both human and animal research. These substances include withanolides, alkaloids, and steroidal lactones (Bhel *et al.,*2022). The intended therapeutic impact, convenience, and personal preference are all important considerations when selecting a dosage form. Depending on the individual health goal and mode of administration, each offers a unique set of advantages and disadvantages. For example, whilst capsules and tablets have the benefit of precision dosing and convenience of transportation, powders and extracts, for instance, frequently enable faster absorption and rapid results (Abozaid *et al.,* 2024). Parallelly, the rise of e-commerce has made online customer reviews a valuable tool for understanding post-purchase behaviour, especially in the health and wellness sector. Subjective reviews of products that deal with mental health issues, such as ashwagandha-based supplements that lower anxiety, are often collected and can be analysed to determine consumer sentiment. Protein powders, vitamins, weight-loss products, probiotics, and general nutraceuticals are just a few of the vast categories of dietary supplements that have been the subject of recent sentiment analysis studies on health and wellness products. Usually, these studies highlight:

- Sentiment classification based on polarity (positive vs. negative)
- Models for star-rating predictions, Systems for recommending products
- Metrics for overall customer satisfaction

A few significant gaps still exist, though:

- Insufficient emphasis on Ayurvedic products and herbal adaptogens. Although vitamins and nutraceuticals have been extensively researched, little empirical study has been done on how consumers feel about Ayurvedic or adaptogenic herbs, especially supplements containing ashwagandha.
- Absence of emotion-level analysis in studies on herbal supplements. Instead of using multi-dimensional emotional analysis (e.g., trust, anticipation, dread, disgust), the majority of current research relies on polarity (positive/negative) classification. In goods that address mental health disorders like anxiety, where consumer perception is highly subjective and emotional, emotional granularity is particularly crucial.
- Sentiment analysis is not sufficiently integrated with the value-chain and agribusiness perspectives. Hardly have previous sentiment studies linked consumer emotional insights to wider ramifications for the agricultural and herbal supply chains. Understanding digital consumer input has consequences for branding, pricing, and farmer-level value realization because ashwagandha is both an agricultural commodity and a medical herb.
- Herbal products of Indian origin are underrepresented in digital review analytics. Few studies systematically analyze internet reviews of Indian herbal supplements using structured NLP methods like the Syuzhet lexical framework, despite India being a global hub for Ayurvedic items.

Methodology

This study uses an ex post facto research design, meaning that the dependent variable, or consumer sentiment, is observed first, and the independent variable, or product usage, has already occurred. Sentiment analysis of anxiety-relieving products, with an emphasis on ashwagandha supplements, is the main goal.

Source of Data and Selection Standards

The primary data for this study were obtained from Amazon India (www.amazon.in), a prominent e-commerce platform extensively utilised for acquiring herbal and dietary supplements. The platform was chosen for its significant user base and comprehensive availability of customer evaluations in the health and wellness sector. To maintain the relevance of consumer perceptions, only latest published reviews were included for examination. Product selection was based on the keyword search term "Ashwagandha anxiety relief" in the Health and Personal Care category. Products were considered if they contained Ashwagandha (Withania somnifera) as a key active ingredient, were classed as herbal or dietary supplements, received at least 100 customer evaluations, and were available for purchase throughout the data collecting period. Only capsule, pill, or extract-based supplement formulations designed for stress or anxiety management were examined.

Review-level inclusion criteria were used to assure data quality and consistency. Only English-language reviews with meaningful textual content were kept. Reviews required to be related with verified purchases and fall inside the specified time frame. The dataset removed reviews that contained only star ratings without text, duplicate entries, non-English comments, and reviews shorter than five words. After applying these criteria, 200 reviews were selected for sentiment analysis.

Multiple metadata fields were stored for each selected review, including the review text, star rating (1-5 scale), date of review, confirmed purchase status, product brand name, and number of helpfulness votes. The analysis relied solely on publicly available information from the Amazon platform. No private information was accessed, and no interaction with reviewers happened. To guarantee confidentiality, data were only utilized for academic study and evaluated in aggregate form. The study followed conventional ethical norms for internet-mediated research, and no attempts were made to identify or contact individual participants.

The final dataset was composed of 200 reviews that met predefined inclusion criteria. The sample size was established using two methodological considerations. First, lexicon-based sentiment analysis often requires adequate textual diversity rather than large-scale numerical datasets, and previous studies in online consumer sentiment analysis have shown that meaningful emotional patterns can be extracted from samples ranging from 150 to 300 reviews. Second, a preliminary saturation study revealed that after around 170 evaluations, no significant new high-frequency lexical patterns appeared, indicating topic saturation. As a result, 200 reviews were deemed appropriate to represent major emotional structures while remaining analytically manageable. To improve robustness, future studies may broaden the dataset to include multiple brands, longer time periods, or cross-marketplace comparisons.

To improve methodological rigor, a manual annotation validation subset was created to compare automated sentiment classification to human interpretation, addressing contextual ambiguities inherent in lexicon-based approaches. The inter-rater agreement was determined to maintain consistency and reduce subjective bias in manual coding. Model performance indicators were presented to objectively evaluate categorization accuracy. Furthermore, a second sentiment analysis strategy was used to enable methodological triangulation and reduce single-method bias. These steps improve the internal validity, repeatability, and robustness of the findings.

Before sentiment analysis, the raw review texts were rigorously preprocessed with R (tidytext, tm, and stringr packages) to ensure consistency, noise reduction, and analytical correctness. To ensure uniformity, all text was changed to lowercase. Punctuation marks, special characters, numeric tokens, URLs, emoticons, and other non-alphanumeric characters have been removed. To decrease linguistic noise, standard English stop words (for example, "the," "is," "and") were removed using a specified stopword list. The cleaned text was then tokenized into individual words (unigrams) to aid lexicon matching. Where appropriate, stemming was used to reduce terms to their base forms, therefore consolidating lexical variations. To increase signal clarity and computational efficiency, phrases with a frequency of less than 2% were deleted. These preparation methods converted the unstructured review data into a structured format appropriate for sentiment scoring.

Sentiment classification was carried out with the syuzhet package in R, which uses the NRC Emotion Lexicon to map individual tokens to ten predefined emotional categories: anger, anticipation, disgust, fear, joy, sadness, surprise, trust, positive and negative. Sentiment scores for each review were calculated by summing the frequency of terms linked with each emotional category. Net polarity at the document level was computed as the difference between positive and negative word counts, but emotional intensity was measured using relative frequency distributions across categories rather than binary labeling. Rather than simply categorizing consumer input as positive or negative, this approach enabled multidimensional emotional profiling.

Given the recognized limits of lexicon-based techniques in managing contextual modifiers, additional emphasis was placed on negation handling. The phrases "not," "no," "never," "hardly," and "without" were detected using a predetermined negation lexicon. When a negation term appeared within a three-word window before a sentiment-bearing word, its polarity was inverted. Expressions like "not effective" and "no relief" were reclassified to represent negative mood, despite the fact that they contained lexically positive elements. This contextual adjustment increased categorization accuracy in reviews of therapy success.

Furthermore, domain-specific vocabulary commonly used in Ashwagandha supplement reviews—such as "KSM-66," "adaptogen," "cortisol," "dosage," and "bioavailability"—is not fully represented in typical sentiment lexicons. To overcome this constraint, high-frequency domain-relevant phrases were found using exploratory frequency analysis and manually inspected. Therapeutic indicators such as "relief," "calm," and "energy boost" were classified as positive health signals, while terms like "side effects," "nausea," and "stomach upset" were classified as negative health indicators. Technical descriptors like "extract" and "KSM-66" were considered neutral unless supplemented by explicit evaluative wording.

To improve contextual sensitivity, the original NRC lexicon was supplemented with additional domain-specific terms detected in the corpus. These supplementary terms were manually coded and added to the sentiment lexicon before final scoring. Validation against a manually annotated subset revealed better alignment between automated classification and human interpretation after lexicon augmentation. These preprocessing and scoring processes improved the methodological transparency, domain relevance, and reproducibility of sentiment analysis.

To make the findings more credible and statistically significant, the study included 95% confidence intervals for the proportion of reviews that expressed each opinion. A confidence interval depicts the range within which the genuine sentiment proportion is expected to fall in the general population. For example, if 71% of reviews showed positive sentiment, the confidence interval shows how precise that estimate is and if it may change somewhat if more reviews were reviewed. This avoids overgeneralization and gives a better sense of the certainty of the results.

Furthermore, sentiment patterns were analyzed across significant subgroups of evaluations. Reviews were classified according to star rating (low: 1-2 stars; moderate: 3 stars; high: 4-5 stars), product form (capsule, pill, or powder), and confirmed purchase status (verified vs. unverified). Statistical tests, such as chi-square tests, were utilized to assess whether sentiment differences between these groups were statistically significant or occurred by chance. Furthermore, logistic regression analysis was used to determine whether rating level, product form, or verification status affected the likelihood of positive or negative sentiment. To assess the strength of these connections, effect sizes were given as odds ratios with confidence intervals.

By presenting confidence intervals and doing subgroup comparisons, the study goes beyond basic description to establish statistically supported conclusions on consumer attitudes toward Ashwagandha supplements.

Preparing and Processing Data

The reviews were handled as raw text data because they were initially written in unstructured sentences. The collected reviews were initially exported using the Amazon Review Export tool and then converted to plain text (.txt) format for further analysis. The textual information was then pre-processed to remove unnecessary characters, punctuation marks, and duplicate entries, ensuring consistency and analytical correctness. Following the pre-processing stage, the review texts underwent dictionary-based sentiment analysis. In this method, the textual content of each review was matched to a predetermined sentiment vocabulary comprising positive and negative words. those related with positive sentiment boosted the positive score, while those connected with negative sentiment lowered it. The aggregate polarity score provided by the dictionary matching technique was used to classify each review as positive, negative, or neutral emotion. The exact search strings used were: "Ashwagandha supplement", "Ashwagandha capsules", "Ashwagandha root extract", "value", "money", "waste", "health effect", etc. Initially, 650 reviews were collected from selected product listings. After filtering the dataset for duplicate entries, non-English reviews, reviews with inadequate textual content, regional language reviews, and Hindi language reviews, a final sample of 200 reviews was chosen for sentiment analysis. Only publicly available review data were gathered, and no personally identifiable information was saved. The data were manually exported and used only for academic research purposes, in accordance with Amazon's platform regulations. Through the use of text mining techniques, this data was cleaned and converted into a structured format appropriate for computational analysis. In order to find significant patterns and insights, text mining also referred to as text data mining involves turning unstructured textual content into data that can be analysed (Liu, 2012).

Method of Sentiment Analysis

To find and categorise user feelings connected to product efficacy, sentiment analysis a method under Natural Language Processing (NLP) was employed. The "syuzhet" package in R, which uses a lexicon-based approach to classify text into ten emotional sentiments such as joy, trust, fear, sadness, and others was used to perform the analysis (Silge *et al.,* 2017).

Visualisation and Analytical Tools

Several statistical and visual aids were used to analyse the sentiment data:

i) Sentiment score representation using bar plots

ii) Using correlation matrices to examine how sentiments relate to one another

iii) Word clouds that show word emphasis and frequency

iv) Word co-occurrence graphs that show relationships between terms that appear frequently

These tools provided insights into the post-purchase behaviour of people managing anxiety symptoms by exposing the emotional tone, recurrent themes, and dominant opinions expressed by users.

The following study done at the Institute of Agri Business Management between 7 February 2025 to 27 April 2025.

Results and Discussion:

The Syuzhet package in R was used to examine customer sentiment. Anger, anticipation, disgust, fear, joy, sadness, surprise, trust, negative, and positive are the ten main emotional categories into which this library's built-in lexicon of positive and negative words aids in the classification of textual data. A thorough sentiment analysis was carried out by grouping words with related meanings into these pre-established sentiments. The final bar graph graphically depicts the general emotional tone of consumer reviews.

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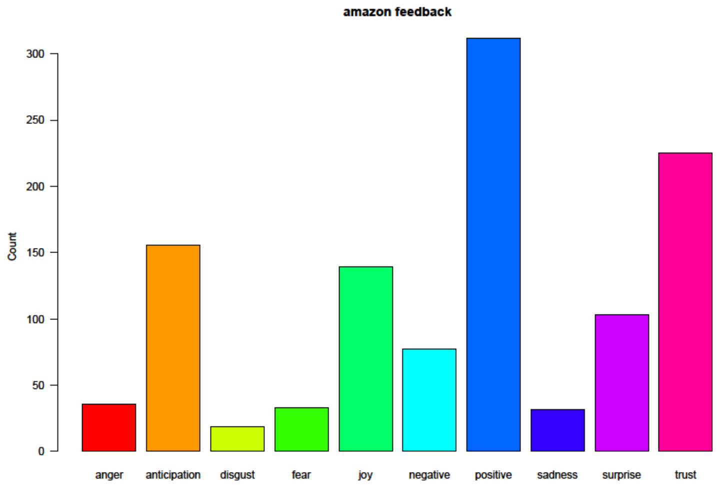

Figure 1: Distribution of Emotional Sentiments in Ashwagandha Reviews

To evaluate emotional responses and product satisfaction, a sentiment analysis of 200 Amazon customer reviews of herbal products that reduce anxiety was carried out. Fig. 1 represents distribution of emotional sentiments in ashwagandha reviews. With "positive" and "trust" emerging as the most prevalent categories, the analysis showed a preponderance of positive sentiments. "Joy" and "anticipation" also suggested positive expectations and results. Notably, there were very few negative emotions like fear, disgust, or rage, indicating that customers were generally satisfied. The word "surprise" alludes to unforeseen advantages or experiences, both good and bad. These results point to a high degree of consumer acceptance and emotional resonance with the product.

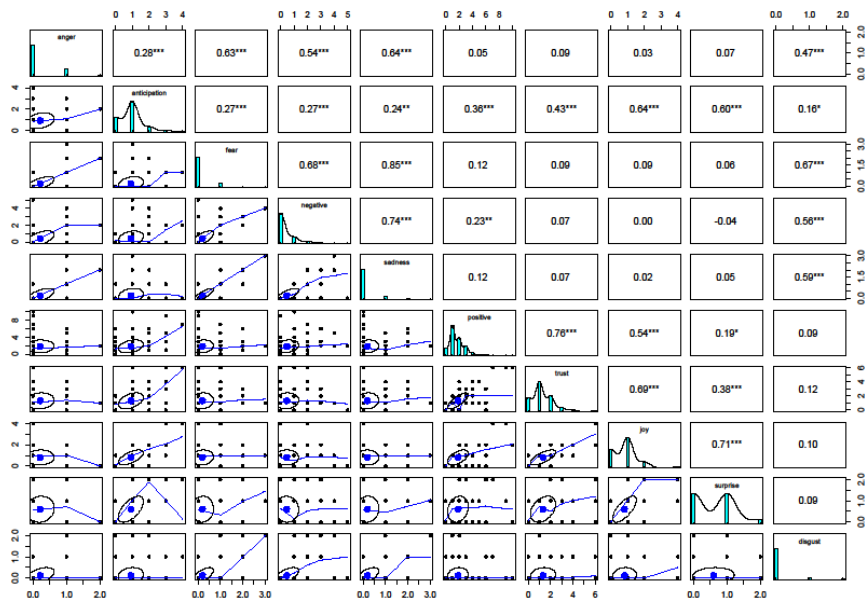

Figure 2: Correlation Matrix of Emotional Co-occurrence Across Reviews.

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Fig. 2 illustrates the Correlation Matrix of Emotional Co-occurrence Across Reviews. The matrix displays the relationships between every possible pair of values in a table. It is an effective tool for identifying and displaying patterns in a large data set as well as for summarising the data. It is frequently displayed as a table, with each variable listed in the rows and columns and each cell containing the correlation coefficient between each pair of variables.

According to the correlation plot, correlation coefficients are powerful when experiencing negative emotions and vice versa. Fear, disgust, and sadness are examples of negative emotions. Joy, surprise, anticipation, and trust are examples of positive emotions.

Bar Plot Showing Contribution of Words to Sentiments

Emotions can be plotted on the X and Y axes, X axes denote word count, Y axes denote the emotion. The top occurring words by word count is displayed. Positive and negative sentiments have their own dictionary according to which the word count is measured.

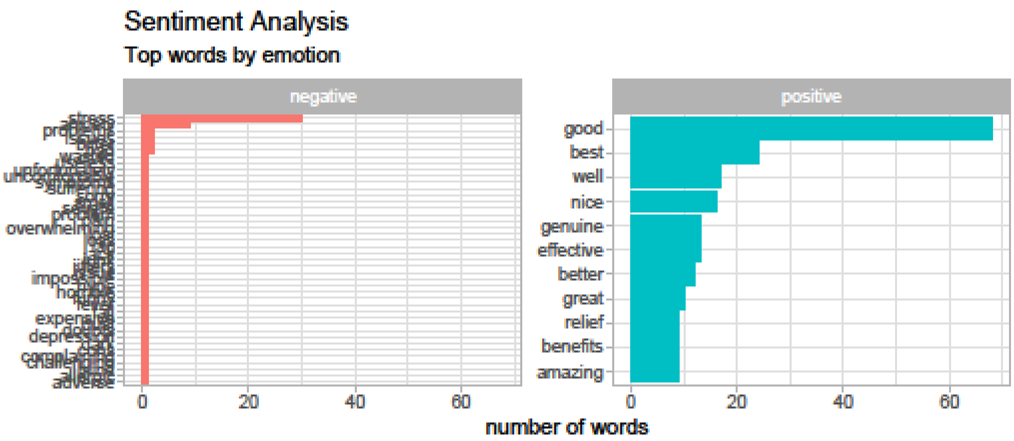

Figure 3: Frequency of Polarity-Contributing Words.

The X and Y axes can be used to plot emotion, with the X axis representing the word count and the Y axis representing the emotion. Fig. 3 shows the frequency of particular words that contribute to both positive and negative emotions was further investigated by the sentiment analysis. Words like good, best, well, nice, genuine, and effective were the most common drivers of positive sentiments, as the graph illustrates, indicating a high level of customer satisfaction and approval. Conversely, negative sentiments were linked to words like "stress," "problem," "issues," "uncertain," and "expensive," underscoring issues with usability, affordability, and dependability. The preponderance of positive language suggests a generally positive impression, even though constructive criticism offers insightful suggestions for development.

Bigrams (two-word combinations) were retrieved following stopword removal and negation processing. Frequent bigrams such as "stress relief," "side effects," "good quality," and "energy boost" were found and ranked according to frequency. This method captures contextual meaning better than single-word analysis.

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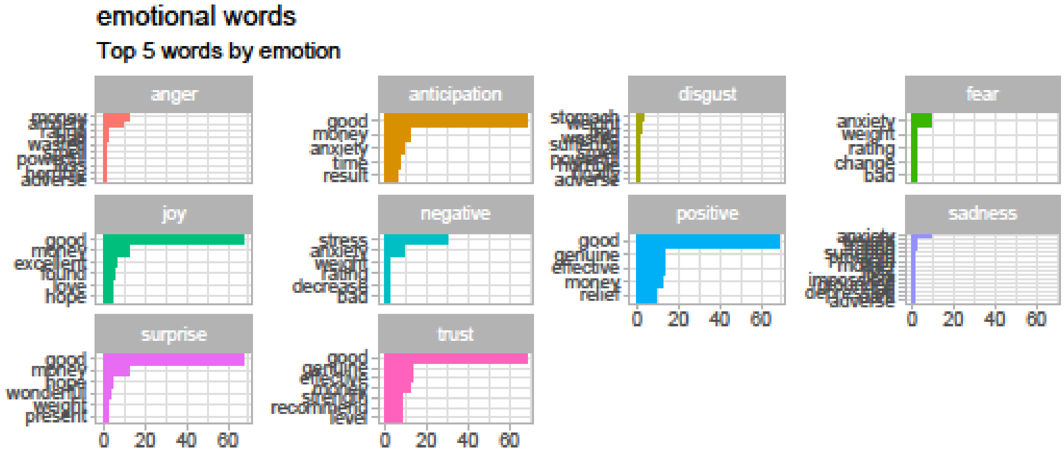

Figure 4: Top Emotion-Specific Contributing Terms.

From the Fig. 4 presented above it can be interpreted that the top five contributing words for each sentiment category are displayed in the emotional word frequency graph. Terms like "good," "money," "genuine," and "wonderful" are commonly used in positive emotions like "joy," "trust," and "surprise," which indicate that customers are satisfied with the effectiveness and value of the product. Words like waited and hope are associated with anticipation, revealing what customers expect before using them. Words like anxiety, waste, problem, weight, and stomach are linked to negative emotions like anger, fear, sadness, and disgust, which indicate perceived inefficiency and health issues. This distribution shows that although sentiment is generally positive, product developers and marketers need to pay more attention to specific emotional triggers related to cost and health.

Frequency Analysis: Word cloud

Using the R wordcloud and wordcloud2 packages, a word cloud was created to show the frequency of important terms in customer reviews. Fig. 5 represents the higher frequency words are highlighted in user sentiment by appearing in larger font sizes. The visualisation illustrates that consumers place the greatest emphasis on terms like "product," "ashwagandha," "good," "stress," and "quality," indicating that they are concerned with overall efficacy, brand recognition, and therapeutic expectations. While terms like stress and anxiety highlight the main issues the product addresses, positive descriptors like best, genuine, relief, and energy further support overall customer satisfaction. The log-odds ratio analysis identifies the most common drivers of positive and negative attitudes in Amazon reviews of Ashwagandha pills. As indicated in Table 1, the word "good" appeared 68 times, with the highest positive log-odds value (4.91), followed by "product" (24 occurrences; log-odds 3.89) and "ashwagandha" (17 occurrences; log-odds 3.55). Other often related positive adjectives include "result" (16), "effective" and "genuine" (13 each), and "quality" (12), all reflecting high customer satisfaction and perceived product effectiveness. Table 2 reveals that unfavorable attitudes were predominantly connected with "stress" (30 occurrences; log-odds −4.11) and "anxiety" (9 occurrences; −2.94), highlighting the product's key health concerns. Additional negative phrases such as "bad," "bitter," "issues," and "problems" featured only twice each, while other words. Additional negative phrases such as "bad," "bitter," "issues," and "problems" appeared only twice apiece, with additional words appearing only once, showing that negative input was restricted. Overall, positive terms have a larger frequency and stronger log-odds values than negative words, indicating that consumer impression of Ashwagandha supplements is overwhelmingly positive.

Table 1: Log-odds ratio of the most frequently occurring words in positive Amazon reviews of Ashwagandha supplements based on Bing sentiment classification

S. No.	word	negative	positive	log_odds
1	good	0	68	4.919981
2	product	0	24	3.89182
3	ashwagandha	0	17	3.555348
4	result	0	16	3.496508
5	effective	0	13	3.295837
6	genuine	0	13	3.295837
7	quality	0	12	3.218876
8	great	0	10	3.044522
9	amazing	0	9	2.944439
10	benefits	0	9	2.944439
11	relief	0	9	2.944439
12	easy	0	8	2.833213
13	energetic	0	8	2.833213
14	pure	0	8	2.833213
15	recommend	0	8	2.833213

Table 2: Log-odds ratio of the most frequently occurring words in negative Amazon reviews of Ashwagandha supplements based on Bing sentiment classification

S. No.	word	negative	positive	log_odds
1	stress	30	0	-4.110874
2	anxiety	9	0	-2.944439
3	bad	2	0	-1.609438
4	bitter	2	0	-1.609438
5	issues	2	0	-1.609438
6	problems	2	0	-1.609438
7	adverse	1	0	-1.098612
8	allergic	1	0	-1.098612
9	blind	1	0	-1.098612
10	challenging	1	0	-1.098612
11	complaining	1	0	-1.098612
12	cons	1	0	-1.098612
13	dark	1	0	-1.098612
14	depression	1	0	-1.098612
15	doubts	1	0	-1.098612

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Figure 5: Word Cloud of Most Frequent Tokens (Minimum Frequency ≥ 10).

Using the R wordcloud 2 package, as shown in Fig. 6, a second word cloud was created to further highlight the linguistic patterns in customer reviews. The most common terms linked to consumers' experiences with anxiety-relieving products are highlighted in this graphic. Strong customer satisfaction and expectations from the product are indicated by prominent words like "good," "stress," "results," "quality," and "will." The presence of brand-related words like rasayanam and KSM suggests notable brand recognition among consumers. Positive adjectives like "genuine," "natural," "effective," and "energy" convey both the product's therapeutic purpose and the users' emotional bond with it. Understanding consumer priorities and perceived benefits is aided by such lexical patterns.

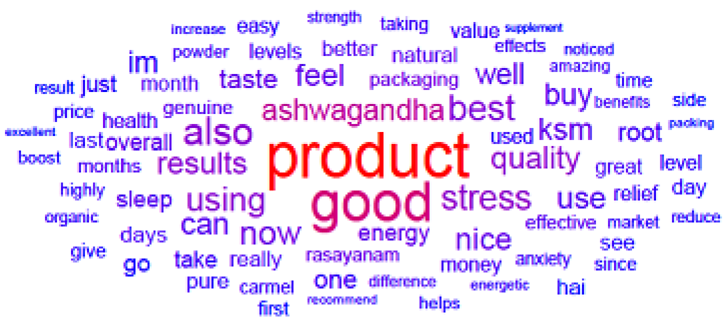

Figure 6: Secondary Word Cloud with Domain-Specific Emphasis.

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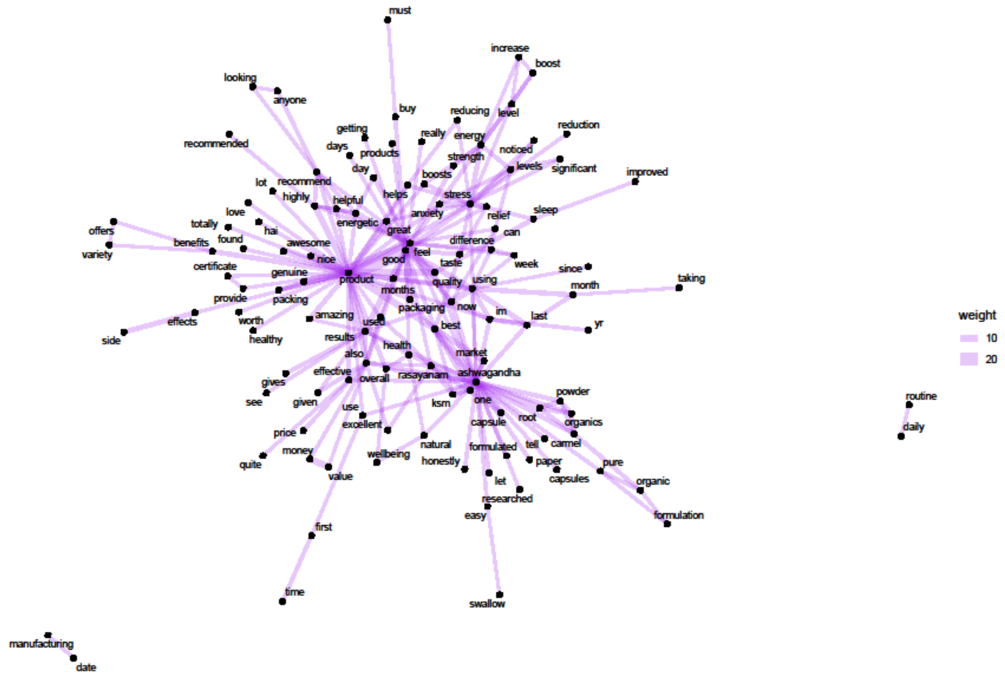

Figure 7: Word Co-occurrence Network (Window Size = 3 Tokens).

Fig. 7 represents the network of co-occurring words. A word co-occurrence network was created in order to investigate more complex relationships between terms in customer feedback. This graphic illustrates the frequency with which words occur together in a given context, creating clusters of related meanings. The edges show co-occurrence relationships; the thicker and closer the edges, the stronger the association. Each node represents a distinct word. Words like "product," "good," "ashwagandha," and "results," which are central and highly connected, emphasise their predominance in several feedback entries. The dense central cluster indicates that the performance of the product and emotional outcomes like "relief," "stress," and "energy" are the main areas of consumer sentiment. This type of network analysis supports more focused marketing and product improvement strategies by providing deep insights into the semantic structure of consumer opinions in addition to sentiment.

Conclusion:

Sentiment analysis of 200 Amazon reviews was performed using syuzhet package, which classified text into ten emotional categories such as positive, negative, trust, delight, and anticipation. The data show that consumers have a generally positive attitude toward anxiety-relieving herbal treatments, with words like optimistic, trust, joy, and anticipation showing the most frequently. The lack of negative feelings suggests that users had a positive experience and were satisfied. Overall, the findings indicate that consumers have significant confidence and affective acceptance of herbal treatments for anxiety control.

The correlation matrix of emotional co-occurrence shows the correlations between the various sentiments stated in customer reviews. According to the findings, positive emotions like as joy, trust, anticipation, and surprise frequently occur together, whereas negative emotions such as fear, disgust, and sadness are also strongly related. This trend suggests that customer encounters are typically divided into distinctly favorable or negative emotional responses. Overall, the dominance and interconnection of positive emotions contribute to the favorable view and adoption of herbal remedies for anxiety management.

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The study of word frequency reveals the emotional drivers that influence consumer perceptions of anxiety-relieving herbal remedies. Positive attitudes were strongly connected with phrases like good, best, well, nice, genuine, and effective, indicating high levels of customer satisfaction and perceived product benefits. In contrast, negative attitudes were associated with phrases such as stress, problem, issues, uncertain, and expensive, reflecting concerns about usability, affordability, and reliability. Despite these limitations, the language utilized in the reviews is mainly positive. Furthermore, the evaluation of common bigrams such as stress relief, side effects, good quality, and energy boost revealed additional contextual insights into customer experiences, validating the overall positive opinion of herbal therapies for anxiety management.

The word frequency and log-odds ratio analyses show that consumer reviews of Ashwagandha supplements are highly favorable. Customers place a high priority on product efficacy and reliability, as seen by the frequent use of terms like product, ashwagandha, good, and quality. Positive terms such as "good" (68 occurrences), "product" (24), and "ashwagandha" (17) are strongly associated with favorable ratings, indicating great satisfaction and perceived benefits. Negative attitudes, on the other hand, are quite rare and are primarily associated with phrases such as stress (30 occurrences) and anxiety (9), which highlight the product's significant health concerns. The low prevalence of other negative phrases shows that dissatisfaction is minor. Overall, the data show that consumers have a high level of trust in Ashwagandha supplements for stress and anxiety management.

The secondary word cloud displays the key phrases that influence consumer views of Ashwagandha-based anxiety treatment solutions. Product, good, stress, results, and quality are the most frequently used words, showing that consumers rate the product primarily on its effectiveness in stress reduction and overall quality. Terms such as ashwagandha, best, and using emphasize active product use and favorable user experiences. Additional words such as sleep, energy, and advantages imply reported increases in well-being, whilst brand-related phrases such as KSM and rasayanam indicate notable brand recall. Overall, the linguistic pattern shows that consumer comments are primarily about product effectiveness, health advantages, and contentment, reinforcing a favorable perception of Ashwagandha supplements.

The word co-occurrence network displays the significant thematic linkages found in customer reviews for Ashwagandha products. Central and closely related phrases such as product, good, ashwagandha, and outcomes suggest that consumer interactions are mostly about product effectiveness and overall experience. The dense clustering of related phrases such as stress, relief, and energy indicates that users typically associate the product with increased well-being and stress management. Overall, the network structure shows that consumer opinion is heavily focused on perceived advantages and outcomes, which provides useful insights for enhancing product positioning, marketing methods, and future product development.

Practical implications and a responsible post-market monitoring framework

This study's findings have various practical consequences for stakeholders in the dietary supplement ecosystem, including manufacturers, marketers, agricultural managers, and regulatory observers.

First, the prevalence of trust, anticipation, and positive attitude indicates that consumer confidence is critical in Ashwagandha-based dietary supplement purchasing decisions. Brands can build trust by increasing transparency about ingredient standardization (e.g., extract type, withanolide %), dose clarity, and sourcing data. Given that price-related worries and terms like "expensive" and "waste money" emerged in negative sentiment clusters, unambiguous value communication and evidence-based positioning may help decrease perceived financial risk.

Second, stratified analysis found that lower-rated reviews were more likely to mention side effects and perceived inefficacy. This emphasizes the significance of managing customer expectations. Instead of making exaggerated benefit claims, marketing communications should focus on responsible usage, acceptable dosage levels, and probable diversity in individual reactions.

Third, domain-specific bigram analysis (e.g., "stress relief," "side effects," "not working") shows that customers often rate products based on functional outcomes. Linguistic insights can be used by product makers to improve packing information, FAQ sections, and post-purchase support. For example, providing precise usage durations (e.g., "benefits may be gradual") may prevent frustration caused by unreasonable expectations of instant effects.

From an agribusiness standpoint, strong positive perceptions of Ashwagandha supplements may indicate continuous market demand, hence supporting medicinal plant value chains. However, maintaining product consistency and quality assurance is crucial for retaining long-term consumer trust.

Limitations of the study

Throughout the article, the phrase "Ashwagandha supplements" is used to appropriately reflect the items' regulatory classification. These products are marketed as dietary supplements rather than pharmaceutical treatments, therefore customer feedback in online reviews should not be construed as clinical evidence of therapeutic efficacy. The current study looks at expressed consumer attitude and perceived experiences, not medical efficacy or safety outcomes.

Ashwagandha (*Withania somnifera*) has been studied in clinical trials for its potential adaptogenic and stress-relieving effects. According to several randomized controlled trials, standardized extracts may lead to lower felt stress levels and improved sleep quality when compared to placebo under controlled conditions. However, results differ according to dosage, extract standardization, research duration, and participant characteristics. While rising clinical evidence suggests possible advantages, dietary supplements do not have the same regulatory approval standards as prescription drugs. As a result, consumer views reported in this study should be taken as subjective experiences rather than confirmed clinical outcomes.

Data Availability Statement

This study's data consists of publicly accessible Amazon India customer reviews collected in compliance with the platform's terms of usage. The marketplace's data policies prevent the redistribution of raw review text. However, the R scripts used for data preprocessing, sentiment scoring, negation handling, and statistical analysis can be obtained from the corresponding author upon reasonable request. The manuscript includes a detailed data collecting technique that enables independent replication.

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