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A Study on Female Consumers' Buying Behaviour and Adoption of Cosmetic Products with Special Reference to Nykaa Digital Reviews

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ABSTRACT

This study examines digital consumer responses relevant to cosmetic-product buying behaviour and adoption, using the Nykaa App Review Sentiment dataset. The supplied dataset contains 194,430 Google Play Store reviews divided into a training set of 155,544 reviews and a test set of 38,886 reviews. The variables are review *content* and *sentiment_labels*, with three sentiment classes: positive, neutral and negative. Descriptive analysis of the combined data shows 71.08% positive, 20.11% neutral and 8.81% negative reviews. The findings indicate that the digital consumer experience surrounding a cosmetics-focused platform is predominantly positive, while negative reviews tend to be substantially longer than positive reviews. Frequently occurring terms include products, love, best, nice, delivery, service, experience, order and beauty, suggesting that product experience and service interactions are important dimensions of online cosmetic consumption. The paper develops a conceptual interpretation connecting product/brand perception, digital reviews, trust and perceived value with purchase and adoption behaviour. A critical methodological limitation is that the supplied dataset does not contain gender, age, income or individual purchase variables; therefore, female-specific behavioural conclusions cannot be statistically established from this dataset alone. The study consequently treats female consumers as the conceptual population of interest while interpreting the Nykaa reviews as digital consumer evidence rather than as a gender-identified survey sample.

Keywords: Female consumers; cosmetic products; buying behaviour; adoption; Nykaa; online reviews; sentiment analysis; e-commerce; consumer behaviour.

1. Introduction

The cosmetics market has become increasingly connected with digital retail, mobile applications, social commerce and consumer-generated reviews. Consumer behaviour in this sector is shaped not only by traditional attributes such as price, quality, packaging and brand image but also by online information, convenience, trust, service experience and peer-generated content (Kotler & Keller, 2016; Schiffman & Wisenblit, 2019; Solomon, 2018). For women consumers in particular, cosmetics may be connected with personal grooming, self-expression, identity and perceived value. Recent studies of female cosmetic consumers in India have examined brand perception, customer satisfaction, social media marketing, product quality and online purchase behaviour (Badgujar & Sinha, 2025; Peter et al., 2025).

Online reviews are especially relevant because they represent post-use or post-service expressions that can influence other consumers' perceptions. Electronic word-of-mouth can affect information adoption and purchase intention, particularly when consumers perceive the information as useful and credible (Erkan & Evans, 2016; Ismagilova et al., 2020). Review platforms also provide firms with an observable stream of consumer feedback that can be analysed at scale. In the cosmetics context, this is relevant because consumers often compare products, brands, prices and service experiences before purchasing.

The present study uses the supplied Nykaa App Review Sentiment train/test data. The Kaggle dataset is described as Google Play Store reviews of the Nykaa e-commerce application collected through August 2021 and labelled positive, neutral or negative according to star-rating groups (Nykaa App Review Sentiment, 2021). The dataset therefore provides a useful secondary source for studying digital consumer experience around a cosmetics-focused e-commerce platform.

The research problem arises from a mismatch between a female-consumer research title and a dataset that does not identify respondent gender. Rather than creating unsupported gender-specific claims, this paper explicitly separates the conceptual population from the observed data. The empirical component focuses on review sentiment, review length and recurring themes, while the female-consumer component is used to frame the broader consumer-behaviour problem. This distinction strengthens the validity of the conclusions.

The study contributes in three ways. First, it documents the composition of the supplied train and test datasets. Second, it provides descriptive evidence about sentiment and review characteristics. Third, it connects digital review evidence to established consumer-behaviour constructs such as attitude, perceived value, social information, trust and purchase intention (Ajzen, 1991; Yang & Peterson, 2004; Hajli, 2015).

2. Objectives of the Study

1. To examine the sentiment profile of consumer reviews associated with the Nykaa cosmetics-focused digital platform.
2. To compare the characteristics of positive, neutral and negative reviews.
3. To identify recurring consumer-experience themes from the review text.
4. To develop a conceptual explanation of how digital reviews may relate to cosmetic buying behaviour and adoption.
5. To identify the methodological requirements for future female-specific primary research.

3. Review of Literature

Consumer buying behaviour is commonly explained as a process involving need recognition, information search, evaluation, purchase and post-purchase evaluation. The Theory of Planned Behavior (TPB) proposes that behavioural intention is associated with attitude, subjective norms and perceived behavioural control (Ajzen, 1991). In an online cosmetics setting, product information, peer reviews, influencer content and perceived convenience may shape these components. Fishbein and Ajzen (1975) provide the earlier attitudinal foundation for linking beliefs with behavioural intention.

Perceived value and satisfaction are also important. Yang and Peterson (2004) show that perceived value and satisfaction are related to customer loyalty, while Jiang et al. (2013) highlight the importance of perceived convenience in online shopping. In cosmetics, consumers may simultaneously consider functional value, emotional value, health/safety considerations and environmental attributes. Research on organic personal-care products found support for several perceived-value dimensions in explaining attitudes toward repurchase (Kim & Ko, 2012).

Digital reviews constitute a major form of electronic word-of-mouth. Hennig-Thurau et al. (2004) conceptualised consumer-opinion platforms as a channel for online word-of-mouth. Chevalier and Mayzlin (2006) demonstrated that online reviews can be associated with sales outcomes, while Zhu and Zhang (2010) showed that the effects of online reviews vary by product and consumer characteristics. Meta-analytic evidence also indicates a meaningful relationship between eWOM communication and purchase intention (Ismagilova et al., 2020).

Social media adds another layer to cosmetic consumption. De Veirman et al. (2017) studied Instagram influencers and brand attitudes; Djafarova and Rushworth (2017) examined online celebrities and young female users; and Sokolova and Kefi (2020) examined credibility and parasocial interaction. Recent cosmetic-specific studies similarly investigate social-media marketing, influencers, brand perception and female purchase intentions (Peter et al., 2025; Shahina Begum & Israel, 2025). A 2026 study of female online cosmetic consumers used an extended TPB model and reported positive associations involving social-media usage, influencer credibility and social-media marketing with TPB components.

Indian evidence is also increasingly focused on women consumers. Research in Gujarat has examined brand perception, satisfaction, trust and online cosmetic buying behaviour among female consumers (Badgujar & Sinha, 2025). Research in Ludhiana reported attention to price sensitivity, discounts, perceived value, self-confidence and personal-image enhancement among female cosmetic consumers. Studies in Punjab and Chennai similarly identify online reviews, quality, brand-related factors, social influence and digital access as relevant to cosmetic or personal-care buying behaviour.

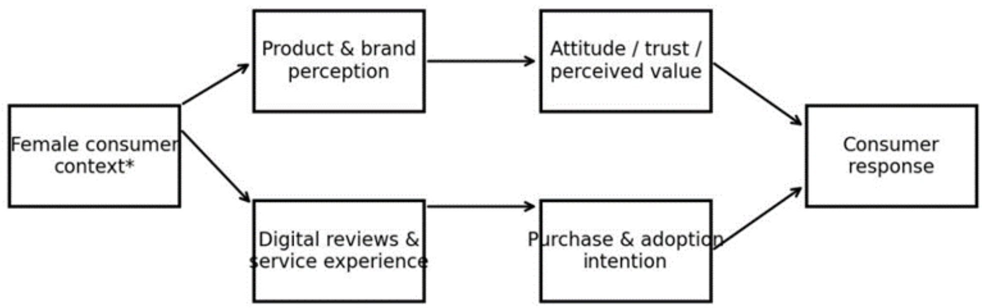
4. Research Gap

A large part of the female-cosmetic literature relies on questionnaire data, whereas app reviews provide naturally occurring digital feedback at much larger scale. Conversely, app-review datasets often lack demographic information required to make female-specific claims. The present study addresses this methodological gap by combining a large-scale text dataset with an explicit limitation statement: the reviews can illuminate digital consumer experience and cosmetic-platform adoption signals, but they cannot independently establish female respondents’ behaviour.

5. Conceptual Framework

The proposed framework integrates consumer-behaviour theory with digital review evidence. Product and brand perceptions may contribute to attitude and perceived value; digital reviews may provide social information and reduce or increase uncertainty; service experience may affect satisfaction and trust; and these constructs may ultimately relate to purchase intention and adoption. TPB provides the behavioural-intention foundation, while eWOM and social-commerce research explain the informational role of online consumer content (Ajzen, 1991; Hajli, 2015; Erkan & Evans, 2016).

Figure 1. Conceptual framework for cosmetic buying behaviour and adoption



*Dataset does not record respondent gender; female-specific inference is therefore a conceptual scope, not a directly observed variable.

Figure 1. Conceptual framework for cosmetic buying behaviour and adoption. The framework is interpretive because the supplied dataset contains no direct measures of the constructs shown.

Proposed hypotheses for future female-only primary data:

H1: Product and brand perception are positively associated with cosmetic purchase intention. H2: Perceived value is positively associated with cosmetic adoption intention.

H3: Trust in digital information is positively associated with purchase intention.

H4: Positive online review exposure is positively associated with adoption intention. H5: Satisfaction is positively associated with repeat-purchase intention.

These hypotheses are propositions for future testing rather than statistically tested hypotheses in the current review dataset.

6. Significance of the Study

For academic research, the study demonstrates how large-scale review data can complement traditional questionnaire studies. For cosmetic retailers, the results highlight the value of monitoring consumer language around products, delivery and service. For future female-consumer research, the study identifies the variables that should be collected directly rather than inferred from app reviews.

7. Research Methodology

A quantitative descriptive and text-analytic design was adopted. The supplied files were inspected independently and then combined for overall descriptive analysis. The training file contains 155,544 records and the test file contains 38,886 records, giving 194,430 reviews in total. Each file contains two variables: *content* and *sentiment_labels*. Seven missing values were identified in the review-content field in the training set; sentiment labels were complete. The text field was therefore treated as the primary observational unit.

The analysis comprised: (1) dataset verification; (2) missing-value inspection; (3) sentiment-frequency analysis; (4) review-length analysis using word counts; (5) recurring-term extraction after basic stop-word filtering; and (6) conceptual interpretation using consumer-behaviour literature. No gender variable was fabricated or inferred from names, language or review content.

Dataset component	Records	Variables	Observed fields
Training set	155,544	2	content; sentiment_labels
Test set	38,886	2	content; sentiment_labels
Combined	194,430	2	content; sentiment_labels
Missing content	7 in training	—	sentiment labels complete

Table 1. Dataset structure and quality check.

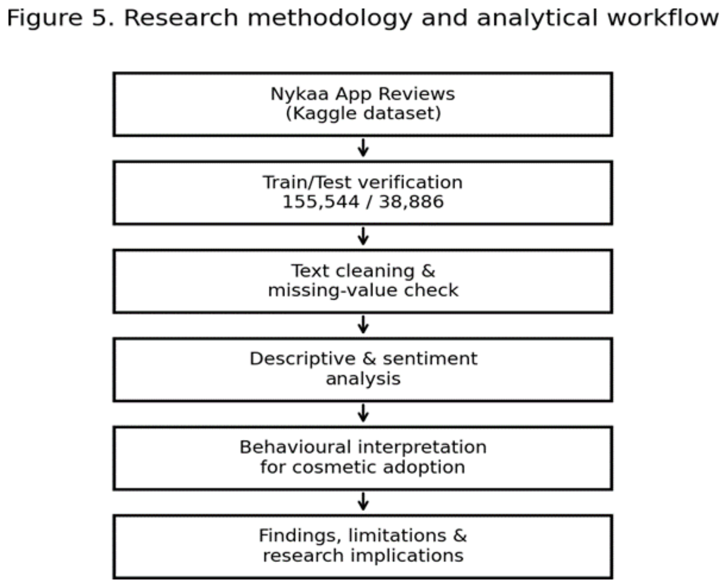


Figure 5. Research methodology and analytical workflow.

The Kaggle dataset description states that the reviews were collected from Google Play Store for Nykaa through August 2021 and that sentiment labels were constructed from star-rating groups. The present analysis therefore interprets the labels as review sentiment rather than as direct measures of purchase adoption.

8. Results and Analysis

8.1 Sentiment distribution

Across the combined 194,430 reviews, positive reviews form the largest category, followed by neutral and negative reviews. The training and test partitions show a similar class structure, supporting their use as predefined dataset partitions. The distribution should not be interpreted as the proportion of female consumers who are satisfied or dissatisfied, because respondent gender and survey sampling information are not available.

Sentiment	Train n	Train %	Test n	Test %	Combined n	Combined %
Positive	110,458	71.02	27,741	71.33	138,199	71.08
Neutral	31,276	20.11	7,821	20.11	39,097	20.11
Negative	13,810	8.87	3,324	8.55	17,134	8.81
Total	155,544	100.00	38,886	100.00	194,430	100.00

Table 2. Sentiment distribution by train/test partition.

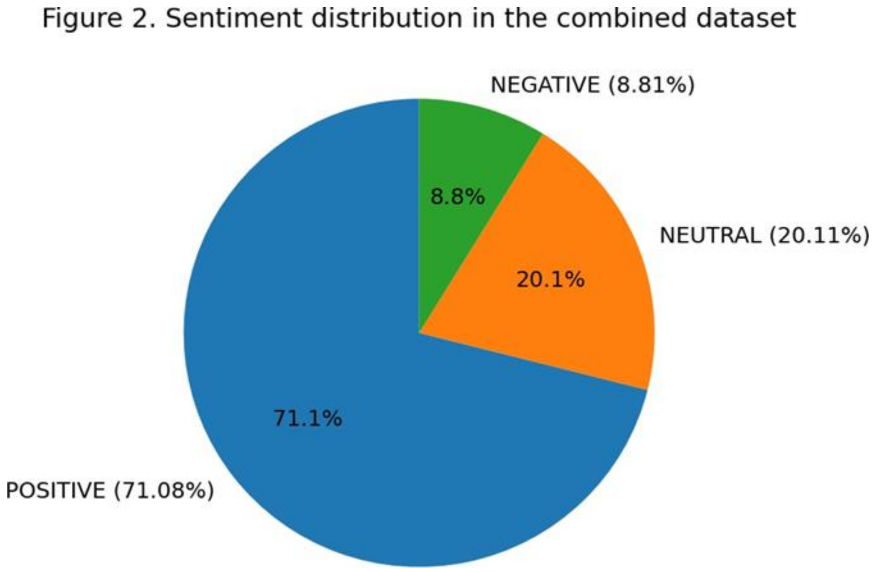


Figure 2. Sentiment distribution in the combined dataset.

The dominant positive class indicates that many users expressed favourable experiences in their app reviews. However, the neutral segment and negative feedback show that the platform also contains mixed and critical experiences. From a consumer-behaviour perspective, such variation is consistent with the idea that online information can provide both supportive and cautionary signals to prospective shoppers (Hennig-Thurau et al., 2004; Zhu & Zhang, 2010).

8.2 Review Length and Information Intensity

The combined dataset has an average review length of 9.35 words and a median of 4 words. The distribution is right-skewed: many reviews are very short, while a smaller number contain detailed narratives. Positive reviews average 6.81 words, neutral reviews 8.62 words and negative reviews 31.59 words. Thus, negative reviews are considerably longer on average than positive reviews.

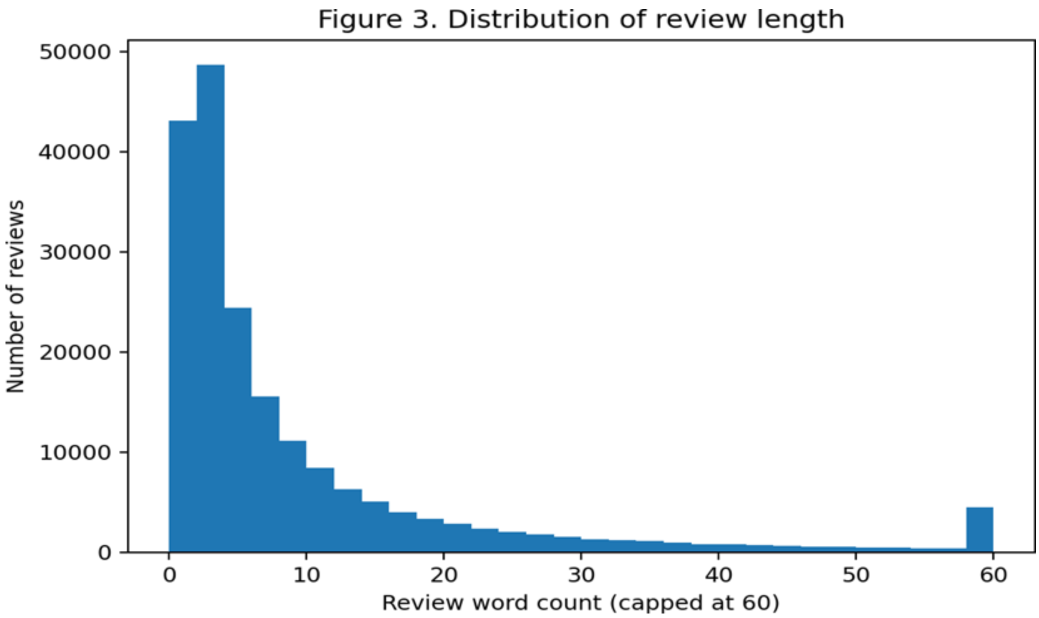


Figure 3. Distribution of review length; the display caps word count at 60 for visual readability.

The difference in review length is relevant to consumer-feedback analysis. Short positive comments may communicate a simple evaluation, whereas negative experiences may motivate users to explain delivery, service, payment, rewards or product-related problems in greater detail. This interpretation is consistent with the broader literature showing that online review content can carry diagnostic information for consumers (Chevalier & Mayzlin, 2006; Ismagilova et al., 2020).

8.3 Recurring Consumer-Experience Terms

After basic stop-word filtering, high-frequency terms included **products, love, best, nice, delivery, great, amazing, service, awesome, experience, order, beauty, offers, genuine** and **customer**. These terms should not be treated as independently validated psychological factors; they are indicators of recurring language in the corpus. Nevertheless, they suggest several meaningful dimensions: product evaluation, emotional reaction, delivery/order experience, service quality, perceived authenticity and promotional value.

The recurring language supports the view that digital cosmetic buying behaviour is not limited to the product itself. The consumer journey includes discovery, evaluation, ordering, delivery, service interaction and post-purchase expression. Omnichannel and social-commerce research similarly emphasises the broader customer experience around digital retail (Verhoef et al., 2015; Huang & Benyoucef, 2013).

8.4 Sentiment and Review Intensity

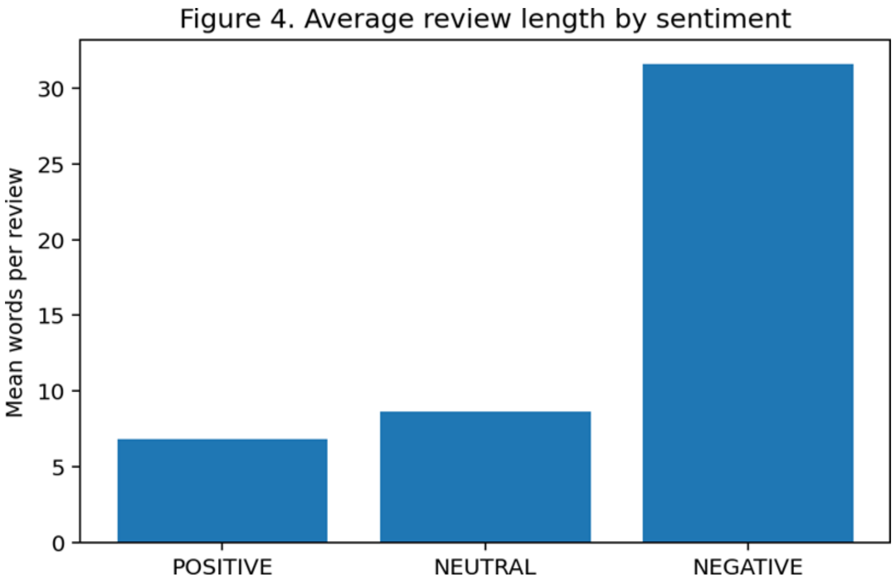


Figure 4. Average review length by sentiment.

The descriptive comparison shows that negative reviews are substantially longer than positive and neutral reviews. This does not prove that negative sentiment causes longer reviews, nor does it prove that long reviews are more useful to consumers. It does, however, indicate that negative feedback may contain richer textual descriptions and may therefore deserve dedicated qualitative or topic-level analysis in future work.

9. Discussion

The findings can be interpreted through the information-adoption perspective. Consumers use available information to reduce uncertainty when evaluating products and sellers. Online reviews can function as social information, and their usefulness may depend on perceived credibility, relevance and diagnosticity (Erkan & Evans, 2016; Ismagilova et al., 2020). In the cosmetics sector, where sensory attributes cannot always be fully evaluated online before purchase, reviews may be particularly useful for understanding expected product and service experiences.

The prevalence of terms related to products, beauty, delivery, service, order and customer experience suggests that digital adoption is multidimensional. A consumer may adopt an app or online channel because it provides product variety and convenience, but continued use may depend on delivery reliability, service responsiveness, offers and perceived authenticity. This interpretation is compatible with research on perceived convenience, social commerce and customer experience (Jiang et al., 2013; Hajli, 2015; Verhoef et al., 2015).

For female-consumer research, social-media and influencer effects should be tested using direct respondent measures. Recent evidence specifically examines female online cosmetic purchase intentions and social-media influences, while other studies examine brand image, credibility and satisfaction in cosmetic purchasing. The present dataset cannot distinguish these effects because it contains no demographic, exposure, purchase-intention or influencer variables.

10. Managerial and Academic Implications

Cosmetic platforms can use sentiment monitoring to identify recurring service and product concerns. Positive reviews can reveal attributes that consumers value, while longer negative reviews may be prioritised for qualitative investigation. For researchers, the results support combining large-scale review mining with female-only surveys to connect observed digital language with measurable attitudes, perceived value, trust and adoption intention.

11. Limitations

First, the dataset contains no gender information; therefore, female-specific statistical claims cannot be made from the supplied reviews. Second, the data represent reviews of a particular digital platform and are not a probability sample of all cosmetic consumers. Third, the dataset description indicates collection through August 2021, so the findings should not be interpreted as a current 2026 market estimate. Fourth, sentiment labels are inherited from the dataset's rating-based construction rather than independently validated human annotations. Fifth, review sentiment is a proxy for consumer expression and does not directly measure purchase frequency, adoption, loyalty, satisfaction, income or demographic differences.

12. Recommended Future Research

A future study should collect primary data from female cosmetic consumers using a structured questionnaire. Recommended variables include age, education, occupation, income, cosmetic-use frequency, monthly spending, product category, brand preference, perceived quality, price sensitivity, perceived value, product safety, social-media exposure, influencer credibility, online-review trust, satisfaction, purchase intention, repeat purchase and adoption intention. A sample of approximately 400–600 female respondents would permit descriptive analysis, reliability testing, factor analysis, correlation and regression; a larger sample could support structural equation modelling.

13. Conclusion

This study analysed 194,430 Nykaa app reviews from the supplied train and test files. Positive sentiment accounts for 71.08% of the combined corpus, neutral sentiment for 20.11% and negative sentiment for 8.81%. Negative reviews are substantially longer on average than positive reviews, and recurring terms point to product experience, delivery, service, ordering, beauty, offers and perceived authenticity as important dimensions of digital consumer expression. These results demonstrate the usefulness of large-scale review data for understanding the digital environment surrounding cosmetic consumption.

At the same time, the paper makes an important methodological distinction: the supplied data do not identify female respondents. Consequently, the evidence supports conclusions about Nykaa digital reviews and cosmetic-platform consumer experience, but not direct estimates of female consumers' buying behaviour or adoption. The most defensible next step is to combine the current review analysis with a female-only primary survey and statistically test the proposed behavioural model.

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