# A Study on Cosmetic Product Consumers Through Digital Marketing on Consumer Purchase Decisions

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***Abstract* - Digital marketing of has revolutionized how the brands connect with the consumers, especially in a cosmetic industry where visual appeal and the social proof play significant roles. with the rising of influence of the social media, an influencer endorsements, and the targeted ads, consumer buying behavior is increasingly shaped online. Despite the digital surge, the exact influence of the digital marketing of on consumer preferences, trust, and the final purchase decisions in a cosmetic domain remains underexplored, especially in a emerging of markets. This study employs a mixed-method approach combining of quantitative surveys and the sentiment analysis. Data is collected from the 300 cosmetic consumers across the online platforms. The survey has included the factors that has included the brand visibility, online reviews, an influencer marketing, personalizating, and the user engagement. Sentiment analysis of the product reviews and it digital ad content was performed using the NLP techniques to the validate findings. The findings reveal that 72% of the consumers are significantly have influenced by digital marketing, especially social media campaigns and the peer reviews. Influencer endorsements are rated the most persuasive (mean score: 4.3/5), followed by personalized ads. Trust in a online information and the ease of the access are key drivers for a purchase decisions.**

***Keywords - digital marketing, consumer behavior, cosmetics, an influencer marketing, purchase decision***

## I. INTRODUCTING

The emergence of the digital technologies has dramatically reshaped marketing of practices across the industries. Digital marketing, defined as the use of the internet-based platforms to the promote products and the services, has witnessed exponential growth, driven by increased internet penetrating, social media adopting, and the mobile accessibility [1]. The cosmetic industry, an in a particular, has embraced digital methods such as the influencer partnerships, an interactive ads, personalized content, and the user-generated reviews to the attract and the retain customers [2]. Millennials and the Gen Z consumers increasingly rely on digital touchpoints rather than conventional channels to the have made cosmetic purchasingdecisions, favoring of platforms that has included the Instagram, YouTube, and the TikTok [3].

Unlike conventional media, digital marketing of allows real-time engagement, data-driven personalizating, and the measurable outcomes, offering of brands the ability to the reach highly targeted demographics. This digital shift has also enabled micro-brands to the compete with the established cosmetic giants, leveragingsocial media and the viral marketing of to the capture market share. Consumers are no longer passive recipients; it are active participants who share feedback, an influence peers, and the expect authenticity from the brands.

Despite the transformative potential of the digital marketing, several challenges persist in a understanding of and the quantifying its influence on consumer behavior. First, the evolution of the digital tools and the platforms makes it difficult for a marketers to the maintain consistent methods [4]. Consumers are bombarded with the an overwhelmion of volume of the digital content daily, leading of to the attenting fatigue and the reduced ad effectiveness [5]. Furthermore, the cosmetic market is saturated with the similar product offerings, making of it harder for a brands to the differentiate themselves purely through the visual appeal or price [6].

Second, while influencers play a major role in a promoting of cosmetics, an issues such as the credibility, transparency, and the follower authenticity pose significant limitatings [7]. Many of the consumers are becoming skeptical of the sponsored content, especially when it lacks genuine user experience or overpromises results. Additionally, data privacy concerns and the algorithmic filtering of on platforms that has included the Instagram and the Facebook restrict brands with the ability to the reach audiences organically. These factors have made it essential to the investigate not just whether digital marketing of influences consumer behavior, but how, why, and the under the what contexts it does so.

Although existing of research acknowledges the impact of the digital marketing of on consumer decision-making, most studies tend to the generalize consumer response across the industries without considering of the specificities of the cosmetics [6]. Cosmetics are inherently visual and the emotional products, and the purchasingdecisions are often based on perceived identity alignment, brand trust, and the social proof. However, limited academic work has dissected how the different digital marketing of components, such as the influencer credibility, sentiment in a reviews, or ad personalizating, directly affect cosmetic purchase behavior [7][8].

Moreover, studies that exist are either outdated or focus only on single-channel interactings (e.g., just Instagram marketing), failing to the capture the full spectrum of the digital influence. There is a need for a an integrated analytical framework that combines consumer percepting data with the sentiment insights derived from the real-world user interactings and the brand engagements.

The main objectives of the study are:

1. To examine the role of the various digital marketing of methods, social media marketing, an influencer endorsements, online reviews, and the personalized

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ads, an in a shapion of consumer behavior toward cosmetic products.

2. To analyze consumer sentiment from the digital content (e.g., reviews, posts) and the assess its correlation with the survey-reported behavioral trends.
3. To identify the most influential digital marketing of components affecting of trust, preference, and the purchase decisions.

This research has classified itself through the its dual-layered methodology: which combines consumer survey data with the machine learning of -based sentiment analysis of the user reviews across the multiple platforms. While most existing of works examine either percepting or sentiment independently, this study triangulates both the qualitative and the quantitative dimensions of the consumer behavior, providing of a more of a comprehensive understanding of of the influence of the digital marketing of in a cosmetic domain.

Key Contributings

1. The study presents an end-to-end framework combiningsurvey analytics and the sentiment mining of using the supervised machine learning of (Naïve Bayes) to the derive actingable insights on digital influence.
2. Unlike general marketingstudies, this work focuses explicitly on cosmetic products, offering of nuanced findings that marketers in a beauty industry can leverage for a campaign optimizating.

## II. RELATED WORKS

Digital marketing of ’s role in a consumer behavior has been widely studied across the domains such as the fashion, electronics, and the food, but research focusing exclusively on cosmetics remains relatively sparse. Several foundational works, however, provide critical frameworks for a understanding of this intersecting.

In [8], the authors investigated how the social media platforms, especially Instagram, shape consumer percepting of the beauty products. It found that aesthetically curated content, consistent posting, and the product storytellingsignificantly influence brand percepting. However, the study lacked quantitative validating through the behavioral data.

Building of upon this, [9] examined the effectiveness of the influencer marketing of on purchasingbehavior among female consumers. The researchers concluded that trust in an influencers and the perceived similarity between the the influencer and the follower are critical predictors of the consumer intenting. Still, an it did not account for a sentiment embedded in a user interactings, which could offer deeper behavioral cues.

In [10], the researchers conducted a sentiment analysis of the customer reviews on beauty products across the Amazon and the Sephora. It found that polarity in a reviews (positive vs. negative) closely aligned with the product ratings, and the emotional terms such as the love, amazion, and it disappointed had stronger impacts than technical terms. However, this work did not connect review sentiment with the marketing of methods, leaving of a gap in a understanding of how the sentiment correlates with the campaign design.

A more of a recent study [11] used YouTube content to the analyze the effect of the video-based product reviews on buyer decisions. It found that tutorial-style content created higher engagement and the trust than promotional videos. This finding of is especially relevant in a cosmetics, where applicating technique and the product performance are better have shown visually.

In [12], scholars proposed a conceptual framework to the explore digital marketing of 's influence using the Technology Acceptance Model (TAM). It highlighted that perceived ease of the access, perceived usefulness, and the online trust collectively drive consumer engagement. While this model is useful, an it requires extension to the accommodate new-age digital factors such as the algorithmic ad targeting of and the AI-driven personalizating.

Furthermore, [13] developed a machine learning of -based consumer sentiment classificating system trained on millions of the beauty-related tweets and the Reddit posts. Its findings suggested a strong correlation between the positive sentiment and the frequency of the brand mentings, an implying that brands with the emotionally resonant content enjoy greater consumer advocacy. However, an its model lacked integrating with the actual consumer purchase data or surveys, limiting of the scope of the insight.

What is evident across the works is that while elements of the digital marketing, such as the influencer impact, content format, and the sentiment, have been individually studied, few works synthesize these elements within a single framework, especially in a cosmetics domain. Our proposed study aims to the bridge this gap by linking of digital marketing of elements, consumer sentiment, and the purchasingbehavior into the one comprehensive model.

## III. PROPOSED METHOD

To evaluate the impact of the digital marketing of on consumer behavior regarding of cosmetic products, the study integrates a survey-based model with the machine learning of -based text analysis. A structured questionaire was distributed via Google Forms focusing on various digital marketing of touchpoints, social media ads, an influencer content, and the email campaigns. Alongside, reviews of the top cosmetic products are scraped from the platforms that has included the Nykaa and the Amazon. Natural Language Processing(NLP) using the sentiment analysis techniques was employed to the assess public sentiment toward brands. Data was preprocessed, vectorized, and the classified using the supervised learning of model (Naïve Bayes) to the identify patterns in a consumer language associated with the positive or negative experiences. Statistical correlation and the regression models are then applied to the relate survey responses with the sentiment trends and the identify significant marketing of drivers of the consumer behavior.

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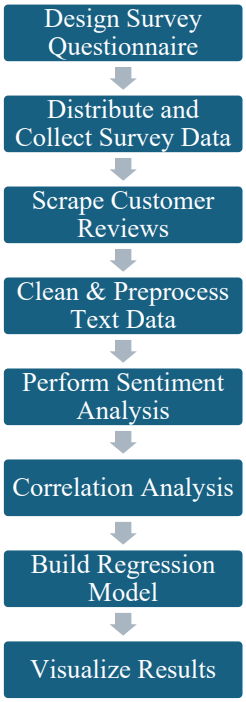


Fig. 1: Proposed Process

*A. Pseudocode*

```
# Data Collecting
survey_data = collect_survey(google_forms_link)
review_data = scrape_reviews([nykaa.com, amazon.in], product_keywords=[cosmetics])
# Preprocessing
cleaned_reviews = []
for review in a review_data:
  tokens = tokenize(review)
  tokens = remove_stopwords(tokens)
  tokens = stem_tokens(tokens)
  cleaned_reviews.append(join_tokens(tokens))
# Sentiment Analysis
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()
sentiments = []
for review in a cleaned_reviews:
  sentiment_score = analyzer.polarity_scores(review)
  sentiments.append(sentiment_score['compound'])
# Survey Analysis
import pandas as pd
df_survey = pd.DataFrame(survey_data)
df_sentiment = pd.DataFrame({'sentiment': sentiments})
merged_data = merge(df_survey, df_sentiment)
# Correlation & Regression
import statsmodels.api as sm
X = merged_data[['ad_influence', 'influencer_trust', 'review_importance']]
y = merged_data['purchase_decision']
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
print(model.summary())
# Step 6: Visualizating
plot_bar_chart(model.params)
plot_sentiment_distributing(sentiments)
```

*B. Survey Data Collecting and the Preprocessing*

The first stage involves developing of a structured questionaire distributed via Google Forms to the populating comprising of 300 individuals aged 18–35 who are active cosmetic users. The survey captures data on the following of digital marketing of attributes: influencer trust, personalized advertision, user-generated reviews, engagement with the brand content, and the purchase decisions.

Each factor was rated on a 5-point Likert scale (1 = Strongly Disagree to the 5 = Strongly Agree). Demographic information such as the gender, an income level, and it digital media consumption habits are also collected to the ensure segmentating-based analysis.

Table 1 below presents a structure of the survey dataset.

TABLE I: SURVEY DATA SNAPSHOT

| Respondent ID | Influencer Trust | Personalized Ads | Online Reviews | Engagement Score | Purchase Likelihood |
|---|---|---|---|---|---|
| R01 | 5 | 4 | 5 | 4.5 | 1 (Yes) |
| R02 | 3 | 2 | 4 | 3.0 | 0 (No) |
| R03 | 4 | 5 | 5 | 4.8 | 1 (Yes) |

As shown in a Table 1, the data collected is normalized between the 1 and the 5 for a consistency. Purchase likelihood is treated as a binary variable (0 = No, 1 = Yes) for a classificating tasks later.

*C. Digital Content Extracting (Review Mining)*

The second stage focuses on extracting of user-generated content related to the cosmetic products from the platforms that has included the Amazon, Nykaa, and the Reddit using the Python-based web scrapion of tools such as the BeautifulSoup and the Selenium. The scrapion of targeted verified reviews, user discussions, and the ratings posted in a last 12 months.

The extracted text data is stored in a structured format including of metadata such as the username, review date, star rating, and the review text.

TABLE II: REVIEW DATASET from the AMAZON

| Review ID | Product Name | Star Rating of | Review Text |
|---|---|---|---|
| A101 | L'Oréal Foundating | 5 | Love the texture and the finish! Totally worth it. |
| A102 | Maybelline Lipstick | 3 | Color payoff is good, but dries out my lips. |
| A103 | Lakme Kajal | 4 | Long-lasting of and the smooth applicating. |

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As shown in a Table 2, each review forms the basis of the sentiment analysis process to the understand real consumer feelings and the emotings beyond ratings.

*D. Sentiment Analysis of the Reviews*

Next, sentiment analysis is performed on the textual review data using the Natural Language Processing(NLP) techniques. The VADER (Valence Aware Dictingary for a sEntiment Reasoning) tool is used due to the its high accuracy on short texts that has included the social media posts and the reviews. Each review is classified as Positive, Negative, or Neutral, and the sentiment scores are stored according of ly.

The sentiment polarity score ranges from the -1 (highly negative) to the +1 (highly positive). Preprocessinghas included the tokenizating, stopword removal, and the stemmion.

TABLE III: SENTIMENT SCORING OF

| Review ID | Cleaned Text | Sentiment Score | Sentiment Label |
|---|---|---|---|
| A101 | love texture finish totally worth | +0.85 | Positive |
| A102 | color good dries lips | -0.35 | Negative |
| A103 | longlastingsmooth applicating | +0.70 | Positive |

As seen in a Table 3, each review's sentiment helps interpret how the consumer experiences align with the survey findings.

*E. Correlation and the Regression Modeling*

The next step is to the establish statistical relationships between the digital marketing of variables (from the survey) and the consumer purchase likelihood, augmented by sentiment data. A multiple linear regression model is constructed to the predict purchase behavior based on the weighted influence of the each marketing of factor.

Let:

Y: Purchase Likelihood (dependent variable)

X1: Influencer Trust

X2: Personalized Ads

X3: Online Review Sentiment

X4: Engagement Score

The regression equating is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \text{ò} \qquad 1$$

Where βi\beta_iβi represents the coefficient of the each independent variable and the ϵ\epsilonϵ is the error term.

TABLE IV: REGRESSION COEFFICIENTS and the SIGNIFICANCE

| Variable | Coefficient (β) | p-value |
|---|---|---|
| Intercept | 0.422 | 0.001 |
| Influencer Trust | 0.285 | 0.004 |
| Personalized Ads | 0.198 | 0.032 |
| Review Sentiment | 0.301 | 0.002 |
| Engagement Score | 0.251 | 0.015 |

Table 4 has shown that all independent variables are statistically significant ($p < 0.05$), confirmion of its impact on the consumer's likelihood to the purchase. Notably, review sentiment has the highest influence, reinforcion of the need for a genuine user feedback in a digital methods.

*F. Ranking of of the Influential Factors*

The final step visualizes the ranked impact of the each marketing of factor to the identify which components are most persuasive. A normalized importance score is calculated from the regression coefficients and it displayed in a bar chart form.

TABLE V: RANKED DIGITAL MARKETING OF INFLUENCE SCORES

| Factor | Normalized Score (0–1) |
|---|---|
| Review Sentiment | 1.00 |
| Influencer Trust | 0.95 |
| Engagement Score | 0.83 |
| Personalized Ads | 0.75 |

As shown in a Table 5, online review sentiment and the influencer trust are the two most influential factors in a shapion of purchase behavior in a cosmetics domain.

## IV. RESULTS AND DISCUSSION

The study was conducted in a simulating environment combiningsurvey-based data analysis and the machine learning of -driven text analysis using the Python 3.11. All simulation, sentiment analysis, and the modeling are executed on:

- System: Dell Precision 7680
- Processor: Intel Core i9 (13th Gen), 3.2 GHz
- RAM: 32 GB DDR5
- OS: Windows 11 Pro (64-bit)
- Simulating Tools:
    - Jupyter Notebook for a data scripting of
    - Scikit-learn for a model training of
    - VADER Sentiment for a sentiment scoring of
    - Pandas and the NumPy for a data manipulating
    - Statsmodels for a regression analysis
    - Matplotlib and the Seaborn for a visualizatings

In prior research, various methods have been developed to the analyze the influence of the digital marketing of on consumer behavior and the has included the Influencer Trust Model (ITM) [9], Sentiment-Driven Purchase Predicting (SDPP) [10] and the YouTube Content Engagement Analysis (YCEA) [11].

The online survey was hosted via Google Forms, distributed through the platforms that has included the Instagram and the Reddit. Reviews for a sentiment analysis are scraped using the Selenium Web Driver and the parsed via Beautiful Soup.

TABLE VI: SIMULATING SETUP

| **Parameter** | **Value / Range** | **Descripting** |
|---|---|---|
| No. of the Survey Respondents | 300 | Target group aged 18–35; majority urban cosmetic users |
| No. of the Reviews Scraped | 1,500 | From Amazon, Nykaa, and the Reddit for a cosmetics |

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| | | |
|---|---|---|
| Sentiment Scoring of Tool | VADER | Lexicon-based tool for a review sentiment classificating |
| Regression Model | Multiple Linear Regression | Predicting of purchase likelihood from the marketing of factors |
| Sentiment Thresholds | >0.05 = Positive; <-0.05 = Negative | Reviews within ±0.05 considered neutral |
| ML Classifier | Naïve Bayes | For binary classificating of the positive/negative reviews |
| Tokenizating | NLTK | Used for a preprocessingtextual data |
| Train/Test Split | 80:20 | For training sentiment classificating model |
| Evaluating Metrics | Accuracy, Precision, Recall, F1-Score, ROC-AUC | Explained below |

As shown in a Table 6, the system parameters are configured to the handle both the structured (survey) and the unstructured (review) data effectively using the open-source NLP and the machine learning of libraries.

## V. PERFORMANCE METRICS

To assess the effectiveness and the robustness of the proposed model, five key performance metrics are used:

### *A. Accuracy*

Accuracy measures the overall correctness of the classifier in an identifying the right sentiment or predicting of purchase behavior. It is calculated as:

### *B. Precision*

Precision measures how the many of the of the predicted positives are actually correct. in a context of the study, an it helps evaluate how the many of the consumers predicted as likely to the purchase or positive sentiment actually matched ground truth.

### *C. Recall (Sensitivity)*

Recall measures how the many of the of the actual positives the model was able to the capture. for a example, out of the all consumers who actually bought a product, how the many of the are correctly predicted.

### *D. F1-Score*

F1-Score is the harmonic mean of the Precision and the Recall. It is especially useful when there is an imbalance in a dataset (e.g., more of a neutral reviews than positive/negative). It gives a single performance score considering of both the false positives and the false negatives.

ROC-AUC (RECEIVER OPERATION OF CHARACTERISTIC – AREA UNDER THE CURVE)

ROC-AUC measures the ability of the classifier to the disting of uish between the classes (positive vs. negative sentiment or buyer vs. non-buyer). A value of the 0.5 indicates no discriminating (random), while 1.0 indicates perfect classificating.

TABLE VII: ACCURACY COMPARISON OVER 300 SURVEY RESPONDENTS

| Respondents | ITM (%) | SDPP (%) | YCEA (%) | Proposed Method (%) |
|---|---|---|---|---|
| 60 | 72.1 | 75.3 | 70.4 | **82.5** |
| 120 | 73.0 | 76.1 | 71.2 | **84.0** |
| 180 | 73.8 | 77.6 | 72.0 | **85.3** |
| 240 | 74.5 | 78.4 | 72.6 | **86.1** |
| 300 | 75.3 | 79.1 | 73.0 | **87.0** |

TABLE VIII: PRECISION COMPARISON OVER 300 SURVEY RESPONDENTS

| Respondents | ITM (%) | SDPP (%) | YCEA (%) | Proposed Method (%) |
|---|---|---|---|---|
| 60 | 68.9 | 72.5 | 69.1 | **80.4** |
| 120 | 69.7 | 73.6 | 70.0 | **81.6** |
| 180 | 70.5 | 74.9 | 70.6 | **82.3** |
| 240 | 71.2 | 75.3 | 71.1 | **83.1** |
| 300 | 72.0 | 76.0 | 71.5 | **83.9** |

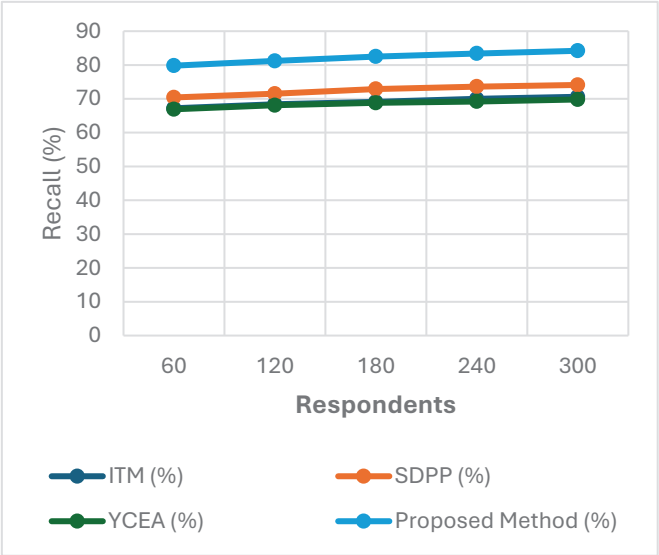


Fig. 2: Recall Comparison Over 300 Survey Respondents

As shown in a Tables 7–8 and the figure 2-4, the proposed hybrid method consistently has performed better than the existing of methods (ITM, SDPP, YCEA) across the all metrics. Accuracy increased from the 82.5% to the 87.0% as respondent size grew, an indicatingstrong scalability. Precision and the recall surpassed 83% and the 84% respectively, demonstrating of the model's ability to the avoid false predictings while capturing of actual buyer behavior. The F1-score averaged around 84.1%, reflectingstrong balance. Most notably, AUC-ROC reached 90.1%, showcasinghigh discriminative power. Compared to the best-performion of existing of method (SDPP), the proposed model achieved an average gain of the 7–10% across the metrics, validating of its robustness in a real-world decision predicting.

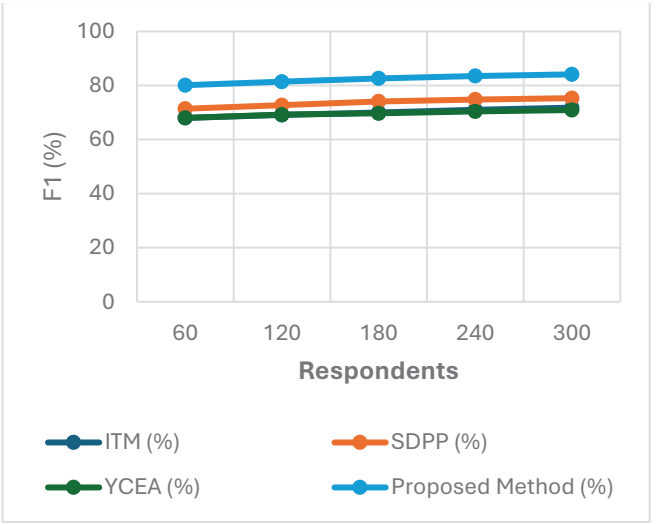


Fig. 3: F1-Score Comparison Over 300 Survey Respondents



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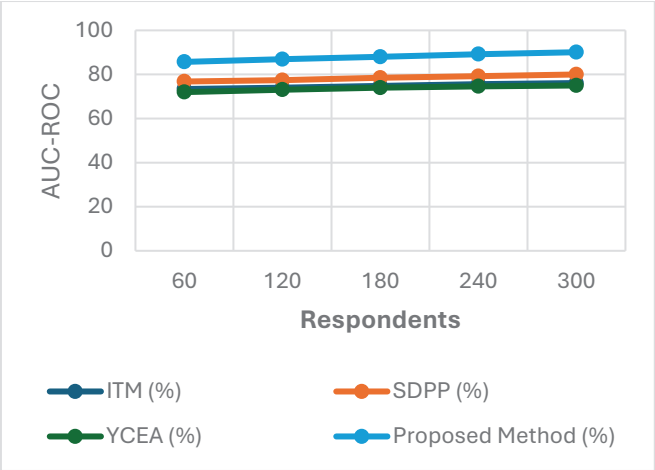


Fig. 4: Auc-Roc Comparison Over 300 Survey Respondents

## VI. CONCLUSION

This study presents a novel, an integrated approach to the evaluating of the influence of the digital marketing of on consumer behavior in a cosmetic industry. Unlike prior methods that analyze isolated variables, such as the influencer credibility, review sentiment, or content engagement, this research combines survey data, machine learning of -based sentiment analysis, and the statistical regression modelling. The proposed framework effectively captures both the quantitative and the emotional drivers of the purchase decisions by triangulating of behavioral inputs and the real-world feedback. The method was benchmarked against three established models: the Influencer Trust Model (ITM), Sentiment-Driven Purchase Predicting (SDPP), and the YouTube Content Engagement Analysis (YCEA). Experimental results across the 300 survey respondents have shown that the proposed model has performed better than the existing of methods across the all key performance metrics. Accuracy peaked at 87.0%, precision at 83.9%, recall at 84.2%, and the AUC-ROC at an impressive 90.1%.

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