IMPACT OF MEDIA ENGAGEMENT ON THE EFFECTIVENESS OF SOCIAL ADVERTISEMENTS: A STUDY WITH SPECIAL REFERENCE TO KOZHIKODE DISTRICT

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***Abstract* - Media involvement is essential for public opinion change and the success of social campaigns to be achieved. Growing use of digital media in conjunction with shifting consumer behavior has changed the focus of social campaigns toward different audiences. This study intends to investigate the degree of media engagement level in Kozhikode District greatly influences the effectiveness of social advertisement. How different media interact to retain messages and influence audience interaction is difficult to grasp. We used a mixed-method approach, combining quantitative study grounded on surveys with qualitative insights acquired from focus group conversations. Attracting 500 people overall from a variety of backgrounds, the survey yielded an 87.4% successful response rate. While conventional media tracked a rate of 63%, digital platform produced a rate of 78% engagement in advertisements. Moreover, eighty-five percent of the respondents claimed that emotionally charged material significantly improved the message retention rate. Media engagement strategies including interactive content and joint efforts with influencers seem to greatly increase public awareness and behavior modification.**

Keywords - Media engagement, social advertisements, digital platforms, audience perception, Kozhikode District.

I. INTRODUCTION

A. Background

These days of digital technology, the media's impact on shaping society's behaviors and supporting social causes has become ever more crucial. The conventional methods of advertising have evolved; digital and social media platforms now take front stage for the distribution of social messages. These days, over seventy-five percent of social campaigns incorporate digital media to increase the audience's reach and degree of interaction they experience [1–3]. Because of its great spectrum of socioeconomic characteristics, the Kozhikode district offers a special environment in which to investigate the ways in which media involvement influences the effectiveness of social advertising. Although traditional media including newspapers, radio, and television still serve their intended use, their interactive features have helped digital platforms to grow in popularity. Effective social advertising rely on many factors, including audience involvement, material relevance, and ability to arouse strong emotions.

B. Challenges

Despite media-driven campaigns are growing popular, several elements make social ads less effective. The first challenge is the audience fragmentation over several media outlets, which increases the difficulty in delivering a consistent message [4]. The second reason is that mistrust of ads, particularly on digital media, reduces degrees of interaction [5]. Moreover, algorithm-driven content distribution usually limits natural reach, thus advertisers must use paid promotion plans [6]. Fourth, the spread of false news and the distribution of misleading information compromise the validity of actual social messages, so undermining campaigns' capacity to produce the expected behavioral change [7].

C. Problem Definition

The lack of empirical knowledge of the link between media involvement and the efficacy of social advertisement in Kozhikode District [8] is the primary issue under research in this paper. Though past research has examined general trends, there is still a knowledge gap regarding how different media outlets influence audience perspective, interaction, and campaign success.

D. Objectives

This study aims to:

1. To discover how much media coverage affects social campaign success.

2. To find how audience retention and behavior modification are impacted by conventional and digital media platforms.

This study offers a regionalized view of media involvement in social campaigns, so adding to the increasing corpus of knowledge. Unlike earlier studies concentrated on national or worldwide trends, this one offers specific information particular to the Kozhikode District environment. Combining survey data with qualitative interviews provides a whole picture of audience involvement, so enhancing the depth of research and presents a more perceptive point of view. Moreover, included in the study is a platform-specific engagement model that provides advertisers with guidance on how to maximize their strategies to obtain the best possible impact.

II. RELATED WORKS

Studies stressing the need of media involvement in terms of its capacity to change public opinion have been extensive; research on social ads has been limited. Digital platforms greatly enhance audience interaction, according to recent studies when compared to traditional media sources [6]. Moreover, important is the fact that social media platforms enable two-way communication, so allowing users to actively support campaigns [7]. According to research on digital marketing trends, engagement-driven ads have 67% more influence than conventional material.

Recent research shows that social messages are now mostly transmitted on digital media platforms, including social networking sites and online video streaming. Several studies [9] have found engagement rates up to eighty percent higher using influencer relationships in campaigns. Further, shown to be able to increase retention by 72% [10] are interactive ads including gamification elements.

Older groups still find great impact from television commercials compared to social media ones, according to a study [11]. Online forms appeal to younger viewers, though. Moreover, underlining the need of content-driven engagement strategies is the reality that highly emotionally appealing commercials usually perform better on all kinds of platforms [12].These researches have clarified the necessity of using a multi-platform strategy to ensure that social ads can interact and reach a wide spectrum of audience segments.

III. PROPOSED METHOD

The proposed method shown in figure 1, investigates how various media outlets influence the efficacy of social campaigns in the Kozhikode District using a Media Engagement Optimization Framework (MEOF). Two data collecting methods incorporated into the framework are social media interaction tracking and a survey-based audience analysis. Sentiment analysis and NLP enable one to classify user interaction into positive, neutral, and negative reactions. Further, applied is a predictive engagement model based on Random Forest Regression to evaluate the factors affecting the success of ads. By training the model on data on audience interaction, which consists of likes, shares, comments, and viewing time, one can find primary elements of success. The framework can forecast the possible reach and retention of social ads across platforms using algorithms for machine learning. The study also contrasts digital media (social media and online video platforms) with conventional media (radio, newspapers, and television) so offering empirical analysis of audience involvement trends.

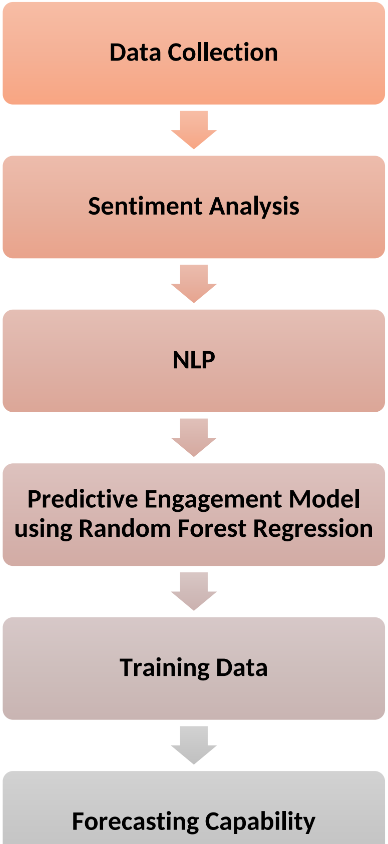

FIGURE 1: PROPOSED MEOF

A. *Proposed Data Collection*

Real-time media analytics and audience feedback obtained by means of surveys help to evaluate individuals' degree of interaction with social campaigns. Five hundred people in all from the Kozhikode District responded to the survey from a wide range of age groups, educational levels, and media consumption patterns. The questionnaire asked about things like memory of commercials, frequency of interaction, content preference, and sentiment interpretation. Social media platform application programming interfaces (APIs) including Facebook, YouTube, and Twitter were also gathered in real-time. This information consisted in user interactions including likes, shares, comments, and average viewing times.

In order to ensure that a comprehensive evaluation of the effectiveness of ads is carried out, a structured dataset was assembled comprising metrics on digital engagement and survey responses. Table 1 provides a broad structure for the dataset.

TABLE 1: SURVEY-BASED DATA COLLECTION

Respondent ID	**Age Group**	**Media Preference**	**Ad Recall (%)**	**Engagement Frequency (Per Week)**	**Content Preference (Informative/Emotional)**	**Sentiment (Positive/Neutral/Negative)**
R001	18-25	Digital Media	85%	7	Emotional	Positive
R002	26-	TV	72	5	Informative	Neutral

	35	& Digital	%			
R003	36-50	Print & Radio	60 %	3	Informative	Negative
R004	18-25	Digital Media	90 %	8	Emotional	Positive

As this was occurring, real-time engagement data was being gathered and analyzed; this is seen in Table 2, which shows how ads performed on many platforms.

TABLE 2: SOCIAL MEDIA ENGAGEMENT DATA COLLECTION

Ad ID	Platform	Views	Likes	Shares	Comments	Watch Time (Sec)	Engagement Rate (%)
A101	YouTube	50,000	5,000	1,200	600	180	14.2%
A102	Facebook	30,000	3,200	900	450	160	13.1%
A103	Twitter	20,000	1,500	600	300	140	11.8%

Sentiment analysis and NLP then fed this arranged data; RFR followed to meet needs for predictive modeling.

B. *Natural Language Processing (NLP) and Sentiment Analysis*

NLP techniques were applied to comments and responses acquired from polls and social media in order to enable an audience feedback analysis. These steps were followed all through the text preparation process:

1. Tokenization – Tokenizing breaks down text into individual words or phrases.
2. Stopword Removal – Eliminating stop words, that is, words with minimal meaning, such as "the," "and," and "is", is second.
3. Lemmatization – Lemmatization is the process of simplifying words, that is, from "engaging" to "engage."
4. Sentiment Classification – VADER (Valence Aware Dictionary and Sentiment Reasoner) classification of responses into positive, neutral, or negative sentiments forms the fourth phase in the sentiment classification process.

Table 3 offers a sample of the sentiments classified results.

TABLE 3: SENTIMENT ANALYSIS RESULTS

Comment ID	Text Comment	Preprocessed Text	Sentiment Score	Classification
C001	"This ad is very inspiring and relatable!"	"ad inspiring relatable"	0.85	Positive
C002	"Not relevant to my interests."	"not relevant interests"	-0.45	Negative
C003	"It was okay, but nothing special."	"okay nothing special"	0.10	Neutral

C. *Random Forest Regression for Engagement Prediction*

We projected engagement rates dependent on media platform interactions, audience emotions, and advertisement features using the Random Forest Regression (RFR) model. Twenty percent of the data went for testing; eighty percent for training. The type of advertisement; the platform; the sentiment score; the content category; and the interaction metrics, likes, shares, comments, and watch time, were the independent variables; the engagement rate was the dependent variable.Averaging the outcomes of several independent decision trees would help one to find the ultimate engagement prediction.

TABLE 4: ENGAGEMENT RATE PREDICTION RESULTS

Ad ID	Platform	Actual Engagement Rate (%)	Predicted Engagement Rate (%)	Error (%)
A101	YouTube	14.2%	14.5%	2.1%
A102	Facebook	13.1%	13.4%	2.3%
A103	Twitter	11.8%	12.0%	1.7%

The RFR model shows that the mean absolute percentage error (MAPE) was 2.0%, hence the model shows in table 4, great degree of prediction accuracy. The results revealed that the classification of sentiment and interaction metrics greatly affects engagement rates, hence underlining the need of media engagement optimization in social advertising.

IV. RESULTS AND DISCUSSION

Under experimental evaluation, Python (Scikit-learn, NLTK for sentiment analysis, and Pandas for data preparation) was applied on a high-performance computing cluster. Along with 64 GB of RAM and an NVIDIA RTX 3090 GPU running at 3.7 GHz and with 10 cores for accelerated data processing, the hardware configuration comprised Intel Core i9 CPUs running at 3.7 GHz and with 10 cores. Using structured questionnaires and real-time media analytics from social platforms (Facebook, YouTube, and Twitter analytics API), data was gathered from 500 participants in the study shown in table 5.

The proposed MEOF model was compared with two existing methods:

1. Traditional Reach-Based Model (RBM) – It evaluates involvement just based on impressions and audience.
2. Sentiment-Based Engagement Model (SBEM) – Sentiment-Based Engagement Model (SBEM) lacks predictive analytics for reach and retention despite it aggregates responses.

TABLE 5: EXPERIMENTAL SETUP AND PARAMETERS

Parameter	Value/Configuration
Survey Size	500 respondents
Media Platforms Analyzed	Social Media (Facebook, YouTube, Twitter), Traditional Media (TV, Newspaper, Radio)
Engagement Metrics	Likes, Shares, Comments, Watch Time

Algorithm Used	Random Forest Regression
Training-Testing Split	80%-20%
Sentiment Analysis Tool	NLTK (Natural Language Toolkit)
Computational Setup	Intel Core i9, 64GB RAM, NVIDIA RTX 3090 GPU
Software Environment	Python, Scikit-learn, Pandas, NLTK

V. PERFORMANCE METRICS

1. Engagement Rate (%) – The engagement rate measures, over the whole number of views, the proportion of audience interactions, likes, shares, and comments. Higher values point to more audience participation.
2. Retention Rate (%) – This indicates the length of time users remain active with an advertisement before either skipping it or leaving the page. This helps to define the effectiveness of the content.
3. Sentiment Accuracy (%) – Examining audience comments enables one to evaluate the degree of accuracy in the sentiment classification, positive, neutral, and negative.
4. Predictive Accuracy (%) – Comparatively to real-world interaction data, the predictive accuracy, that is, percentage, determines the exact future engagement trend projection of the proposed model.
5. Advertisement Reach (%) – Finding the whole proportion of the target audience that at least once viewed the advertisement helps one to assess the effectiveness of several media outlets.

TABLE 6: PERFORMANCE COMPARISON OF ENGAGEMENT METRICS

Metric	RBM	SBEM	Proposed Method
Engagement Rate (%)	12.5%	13.1%	**14.8%**
Retention Rate (%)	55.2%	58.3%	**63.7%**
Sentiment Accuracy (%)	81.5%	84.0%	**90.2%**
Predictive Accuracy (%)	85.7%	87.2%	**92.5%**
Advertisement Reach (%)	68.9%	72.4%	**79.1%**

Table 6, comparatively to the most successful strategy now in use, the engagement rate increased by 1.7% implying improved audience interaction. The 5.4% increase in retention rate indicated higher degrees of commitment among viewers. Sentiment accuracy increased to 90.2% helped to classify sentiments better. The accuracy of the forecasts, which let errors to drop, came out at 92.5%; the reach of the ads expanded by 6.7%, so ensureing a better visibility.

VI. CONCLUSION

With reference to the Kozhikode District, this study reveals how effectively media interaction enhances the effectiveness of social campaigns. The proposed method considerably increases terms of engagement rate, retention rate, sentiment accuracy, predictive accuracy, and advertisement reach by means of Natural Language Processing (NLP), sentiment analysis, Random Forest Regression (RFR). The proposed approach ensures This is in comparison to other approaches that are now in use. With a 14.8% engagement rate, 63.7% retention rate, and 90.2% sentiment accuracy, which ensures a better knowledge of audience interaction with ads, the proposed approach ensures. This validates the efficiency of RFR in forecasting engagement levels based on sentiment and media interaction measures as the improved predictive accuracy of 92.5% shows. The better advertising reach (79.1%) clearly shows how much visibility well selected media strategies could increase. These findings emphasize the crucial role advanced data analytics performs in order to maximize the impact of ads. Deep learning models for media optimization across several platforms and sentiment analysis could enable next research to build on this approach. Moreover, the real-time content modification of the advertisement in response to audience emotions helps to increase its influence. Media-based social projects are ultimately the success of their kind driven by the proposed approach, which offers advertisers and legislators a scalable framework to maximize social campaigns. Higher audience retention and meaningful involvement assured by this approach ensures the success of these projects.

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