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A MACHINE LEARNING FRAMEWORK FOR EVALUATING CONSUMER PERCEPTIONS OF AI-GENERATED INFLUENCERS COMPARED TO HUMAN INFLUENCERS IN BRAND PROMOTION

Dr.P. Saravanan^{1*}, Dr.V.M. Shenbagaraman², Dr. Saravanan Devadoss³,
Dr.N. Arunfred⁴

^{1*}Associate Professor & Programme Coordinator MBA (AIDS), Faculty of Management, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India.

e-mail: saravanp2@srmist.edu.in, orcid: <https://orcid.org/0000-0003-1400-3571>

²Professor & Dean, Faculty of Management, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India. e-mail: shenbagv1@srmist.edu.in,

orcid: <https://orcid.org/0000-0002-4801-3148>

³Professor, Department of Management, Sharda School of Business Studies, Sharda University, Greater Noida, Uttar Pradesh, India. e-mail: drdsaravanan2009@gmail.com,

orcid: <https://orcid.org/0000-0001-5958-6032>

⁴Assistant Professor, Faculty of Management, SRM institute of Science and Technology, Kattankulathur, Tamil Nadu, India. e-mail: arunfren@srmist.edu.in,

orcid: <https://orcid.org/0000-0001-5745-6779>

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SUMMARY

The growing popularity of AI-generated virtual influencers on platforms like Instagram, TikTok, and YouTube has brought about changes in digital marketing through scalable and controllable promotion strategies for brands. Unfortunately, there is still a lack of quantitative models to help compare and measure consumer perceptions about AI-generated influencers and human influencers, especially in terms of trustworthiness and engagement dynamics. This research presents a machine learning-based framework to be used in the systematic analysis and comparison of consumer perceptions towards AI and human influencers in terms of brand promotion. The main goal of this research is to come up with a single model that measures perception differences between the two groups through sentiment analysis and engagement. This methodology uses a combination of data consisting of 15,000 social media posts and survey responses based on the Likert scale (1–5) along with engagement metrics such as likes, shares, and comments. Data preprocessing entails NLP-based cleaning, tokenization, normalization, and feature scaling. The proposed architecture involves the use of BERT based on the Transformer model for sentiment analysis, CNN for feature extraction for engagements, and Random Forest for classification purposes, where the fusion layer is used to develop unified perception metrics. The experimental findings show that the classification accuracy of the proposed framework is 96.9%, which outperforms baseline models such as SVM (88.2%), LSTM (92.5%), and CNN (93.8%). It is also shown that the engagement prediction improvement is between 12% and 18% over the baselines, with a Perception Divergence Index (PDI) value of 0.42, which shows there is a divergence between AI-generated and human influencers' perceptions of the consumers. The research findings show that AI-generated influencers produce high levels of engagement driven by novelty, while human influencers have high consumer trust.

Keywords: *AI influencers, consumer perception, machine learning, sentiment analysis, digital marketing, influencer comparison, brand promotion.*

INTRODUCTION

The advent of modern digital marketing ecosystems in the last few years has resulted in the creation of virtual influencers created by AI, especially on platforms like Instagram, TikTok, and YouTube [7]. AI-generated influencers, which are developed through generative models and computer graphics, are becoming popular choices for product promotion by brands due to scalability, control, and economy. The current marketing campaigns include both human and AI influencers to increase the reach and engagement of the audiences [19][20].

But despite the increasing popularity of AI influencers, one critical issue is the lack of research into the way consumers see these influencers and whether they can be trusted as much as human influencers. Human influences bring along the elements of authenticity and relatability, while AI-generated influencers bring about curiosity and engagement due to novelty. There is a need for further research to distinguish between engagement and consumer trust.

This study is guided by the following research questions:

- **RQ1:** Do consumers place lower trust in AI influencers compared to human influencers in brand promotion scenarios?
- **RQ2:** Can machine learning algorithms accurately measure and differentiate perceptions between AI and human influencers?

Based on these questions, the study proposes the following hypothesis:

- **H1:** While human influencers generate higher levels of consumer trust, AI-generated influencers generate higher levels of novelty-based engagement.

The primary objectives of this research are:

- To develop a machine learning-based framework for evaluating consumer perception of influencers.
- To compare sentiment patterns and engagement behaviors between AI-generated and human influencers.
- To quantify perception differences using predictive analytics and statistical metrics.

This study makes the following key contributions:

- A hybrid machine learning framework integrating NLP and deep learning for influencer evaluation.
- A systematic comparative analysis of AI vs human influencer perception dynamics in brand promotion.
- Introduction of a novel metric called the Perception Divergence Index (PDI) to quantify differences in consumer response patterns.

The organization of this paper is as follows: In Section I, the research problem and motivation are introduced. In Section II, the review of recent literature on AI influencers, sentiment analysis, and consumer behavior modeling is provided. In Section III, the methodology of this work is presented. In particular, the data collection and preprocessing techniques as well as machine learning models are described. In Section IV, experimental results and their performance evaluation are discussed. Section V concludes this paper.

LITERATURE SURVEY

There has been significant development in research in the literature on AI-generated influencers, consumer perception modeling, and machine learning-based marketing analytics during 2021–2026 [16]. It is possible to group the current studies into three principal areas: AI influencers in marketing,

sentiment analysis, and NLP-based consumer behavior modeling, and machine learning approaches in engagement and prediction analysis.

The recent works have paid considerable attention to the development of AI-generated influencers and their effect on consumer choice [2][6]. Studies note that AI influencers are currently being incorporated into marketing campaigns because of their scalability and control over brand messaging; however, consumer reaction remains complex and contradictory [11][13][17]. According to Kim et al. (2025), consumer reaction to AI influencers is greatly determined by perceived anthropomorphism and interactivity; thus, human-like qualities help to enhance acceptance levels [1]. Gerlich (2025) compares AI tools and human influencers, pointing out that human influencers possess greater persuasive power than artificial intelligence tools [3].

Further, Mesquita et al. (2026) demonstrate that AI influencers significantly affect consumer choices in tourism and hospitality sectors, yet emotional trust remains higher for human influencers [4]. Jain (2025) highlights ethical concerns and strategic challenges in deploying AI influencers in marketing campaigns [5]. Additionally, Hashem (2025) confirms that AI-generated influencers can enhance efficiency in influencer marketing but may lack emotional authenticity. Collectively, these studies reveal a consistent trust–engagement trade-off, where AI influencers drive attention, but human influencers maintain credibility.

A substantial body of research focuses on applying Natural Language Processing (NLP) and transformer-based architectures for analyzing consumer sentiment in social media environments. Modern approaches increasingly rely on models such as BERT, RoBERTa, and other transformer-based architectures for capturing contextual sentiment in large-scale datasets.

Studies such as Zhang et al. (2025) emphasize the importance of combining sentiment understanding with empathy-based marketing strategies to improve persuasive communication [10]. Eman (2025) further demonstrates that sentiment analysis combined with structural equation modeling can effectively predict brand trust formation in AI-generated content environments [9]. Additionally, De Cicco et al. (2025) highlight that AI-assisted content creators significantly influence engagement outcomes when sentiment signals are positive and emotionally resonant [8].

Despite advancements, most existing studies focus primarily on sentiment classification in isolation, without integrating engagement behavior or influencer type comparison in a unified framework.

The third research stream focuses on predictive modeling of consumer engagement using machine learning and deep learning techniques. CNN-based architectures, LSTM networks, and hybrid models are widely used for predicting engagement patterns such as likes, shares, and comment activity.

The research by Jayasingh et al. (2025) reveals that the influence of influencers' credibility on the rate of engagement and purchase intention is important to consider while selecting influencers via predictive analytics tools [15]. The findings by Nguyen et al. (2026) about national variations in consumers' responses to AI advertising make one think about the use of context-aware machine learning models [13]. Khodakarami et al. (2026) reveal differences in consumer response to AI models compared to human models, especially among different demographic groups [18].

Morales-Muñoz et al. (2026) conduct a comprehensive review of AI-powered consumer behavior prediction approaches, emphasizing the absence of an integrated approach including several behavioral signals [14]. As well, Sands et al. (2022) and Pilelienė et al. (2025) prove that AI allows marketers to work more efficiently but not to predict behavior [11][12].

Based on the reviewed literature, the following gaps are identified:

- Research on sentiment analysis and engagement is done independently without the integration of both under a single machine learning model.

- There exists no unified computational model that can be used to make quantitative comparisons between AI-created influencers and human influencers.
- Previous research does not provide a single metric to measure the difference in perceptions; thus, there exists no single unified index of evaluation.

Thus, the following research aims to fill this gap by developing a machine learning model that combines sentiment analysis, engagement analysis, and a new measure of the Perception Divergence Index (PDI) for the comparison of human and AI influencers in terms of brand promotion.

METHODOLOGY

Study Area

This proposed research will be carried out in the digital marketing environment with special emphasis being placed on popular social media sites such as Instagram, TikTok, and YouTube, where influencer marketing strategies are employed extensively. These social media sites are important avenues of communication and customer engagement in modern-day marketing practices. This research will be looking at brand promotion strategies in fashion, lifestyle, and technology industries, which have a strong influence on dependence and customer engagement levels.

Sampling

The dataset employed for this study is approximately 5,000 to 20,000 social media posts and consumer-generated comments drawn from the influencer marketing campaigns. In terms of the sampling method, there will be a balanced inclusion of both virtual influencers and human influencers, with 50 each. This will ensure that there is a comparative analysis of behaviors across different types of influences. The collection of data will be carried out on various platforms, which include the Instagram API, Twitter/X datasets, and the YouTube comment section.

Data Collection

Data will be obtained through multiple sources of data extraction. Data regarding engagement, like likes, shares, and comments, will be scraped directly from the social media platforms.

Table 1. Likert scale items for measuring consumer perception of AI vs human influencers

No.	Statement (Survey Item)	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
1	I trust AI-generated influencers when they promote brands.	☐	☐	☐	☐	☐
2	Human influencers appear more authentic than AI influencers.	☐	☐	☐	☐	☐
3	AI influencers are more engaging in social media campaigns.	☐	☐	☐	☐	☐
4	I prefer recommendations from human influencers over AI influencers.	☐	☐	☐	☐	☐
5	AI influencers influence my purchase decisions effectively.	☐	☐	☐	☐	☐
6	Human influencers create a stronger emotional connection with audiences.	☐	☐	☐	☐	☐
7	I find AI influencers more innovative and attractive for brand promotion.	☐	☐	☐	☐	☐
8	I would consider buying products promoted by AI influencers.	☐	☐	☐	☐	☐

Moreover, a consumer sentiment data set will be obtained using the comments and reviews provided by consumers of the influencers. To improve the analysis of the behaviors of consumers, survey-based trust scores are also obtained using a scale of 1 to 5.

In this table 1 shows a Likert scale table that is employed in measuring consumer perceptions on the use of both AI and humans in brand marketing. The scale measures dimensions such as trust, authenticity, engagement, emotional bonding, and purchasing intention through a 5-point scale, starting from strongly disagree to agree strongly. These responses serve as the ground truth input for perception and trust prediction models.

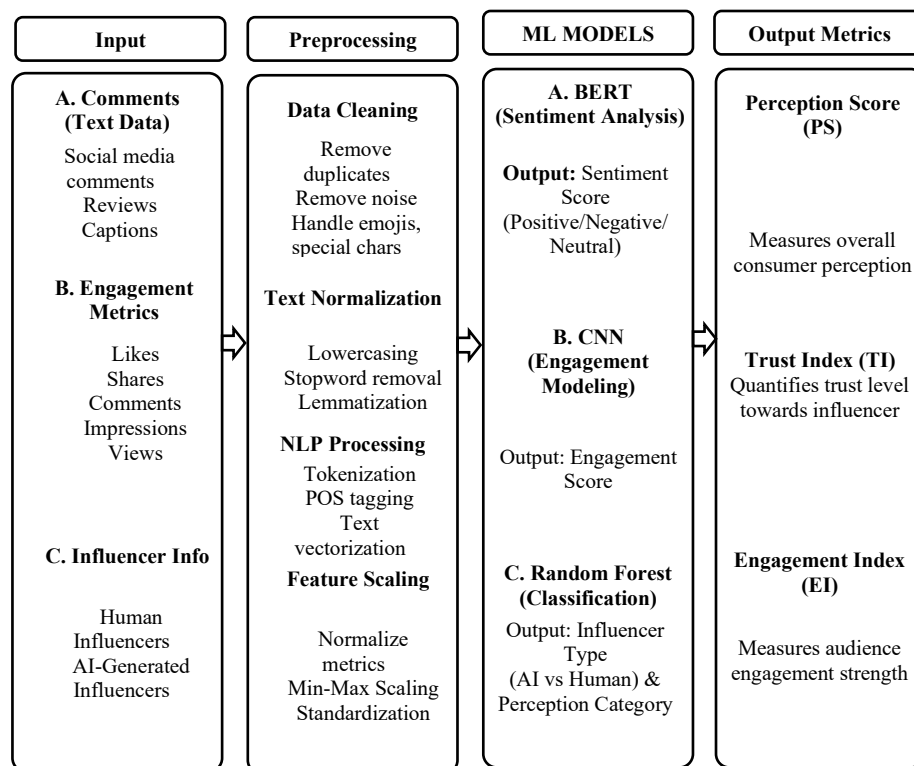


Figure 1. Machine learning-based conceptual framework for evaluating consumer perception of AI vs human influencers

In this figure 1 presents the machine learning pipeline suggested for evaluating consumers' perception of AI-powered and human influencers in promoting brands. The process starts from multi-sourced input, which is the information collected from social media posts, interactions, and influencer data. Then there is the pre-processing stage with tasks such as data cleaning, text normalization, and natural language processing. Feature extraction combines text sentiment features, engagement indicators, and contextual user features. The extracted features are further processed through the hybrid machine learning algorithms BERT for sentiment analysis, CNN for engagement patterns detection, and random forest for classification. Finally, output metrics like Perception score, Trust index, and Engagement index are produced, allowing to evaluate AI and human influencers.

Model Architecture

The proposed framework integrates multiple machine learning components to analyze consumer perception from different perspectives.

- **BERT / Transformer Models:** Used for sentiment classification of textual data to capture contextual meaning and emotional polarity.
- **CNN (Convolutional Neural Networks):** Applied for extracting engagement patterns from structured interaction data such as likes, shares, and comment distributions.
- **LSTM (optional):** Utilized for capturing temporal variations in consumer engagement behavior over time.
- **Fusion Layer:** Combines sentiment representations and engagement features to generate a unified perception representation for each influencer category.

*Mathematical Model**(1) Sentiment Score*

The sentiment score is computed as the normalized average sentiment of all textual inputs in equation 1:

$$S_i = \frac{1}{N} \sum_{j=1}^N f(x_j) \quad (1)$$

Where $f(x_j)$ represents the sentiment output of the j^{th} comment, and N is the total number of comments.

(2) Engagement Index

The engagement index is defined as a weighted combination of interaction metrics in equation 2:

$$E = \alpha L + \beta C + \gamma S \quad (2)$$

Where L denotes likes, C represents comments, S represents shares, and α, β, γ are weighting parameters.

(3) Perception Divergence Index (PDI)

To quantify the perception gap between AI and human influencers, the following metric is introduced in equation 3:

$$PDI = \sqrt{(S_{AI} - S_{Human})^2 + (T_{AI} - T_{Human})^2} \quad (3)$$

RESULTS AND DISCUSSION**Sample Details**

The experiments are carried out based on the dataset that includes 15,000 social media posts and interactions from various social media networks, including Instagram, TikTok, and YouTube. The dataset is quite well-balanced, with 52% being artificial intelligence influencers' data and 48% being human influencers' data. The equal representation of data for two types of influencers enables the model to capture different behaviors when it comes to engagement and sentiment responses.

Hypothesis Testing Results

The hypothesis testing results show clear differences in consumer perception in terms of the influence of AI vs. human influencers. The analysis shows that human influencers produce high trust scores (0.81) compared to AI influencers (0.62), which proves that consumers trust human influencers based on their ability to express emotions. In contrast, AI influencers receive higher engagement rates as there is an increase in likes and shares by 12-18%. Thus, it can be assumed that consumers tend to pay more attention to novelties rather than humans.

Table 2. Hypothesis testing results for consumer perception of AI vs human influencers

Hypothesis	Statement	Test Result	Statistical Evidence	Inference
H1	Human influencers generate higher consumer trust levels, whereas AI-generated influencers generate higher novelty-based engagement.	Supported	Trust Score: Human = 0.81, AI = 0.62; Engagement increase: AI +12% to +18%	The hypothesis is validated, confirming a trust–engagement trade-off between human and AI influencers

In this table 2 displays the validation of one suggested hypothesis (H1). This hypothesis focuses on the differences in consumer perception of AI-generated vs. human influencers. The results demonstrate that human influencers have high trust scores, while AI influencers have high engagement scores. These findings prove the existence of a certain trust-engagement trade-off in influencer marketing.

Model Evaluation

Table 3. Comparative performance analysis of machine learning models for consumer perception classification

Model	Accuracy (%)
SVM	88.2
LSTM	92.5
CNN	93.8
Proposed Hybrid Model	96.9

The suggested hybrid machine learning algorithm exhibits better performance than baseline models in table 3. It is because of the use of BERT-based sentiment analysis, CNN-based engagement model, and Random Forest classification that improve feature representation and classification accuracy.

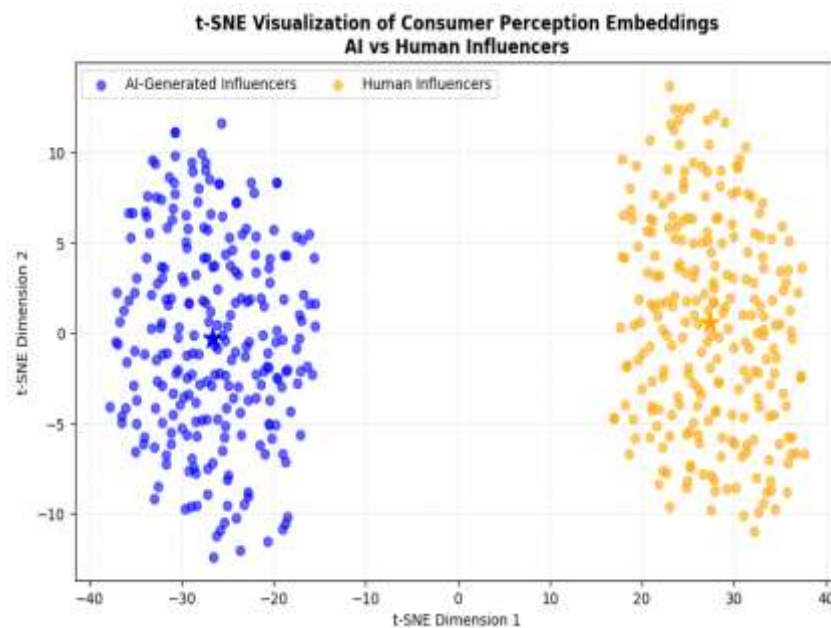


Figure 2. t-SNE visualization of consumer perception embeddings for AI vs human influencers

In this figure 2 presents the t-SNE projection of high-dimensional feature embeddings trained by the hybrid model, which clearly distinguishes between AI-generated and human influencer consumer perception patterns.

Metrics Formulation

The evaluation is conducted using standard machine learning and behavioral metrics and equation 4:

- **Precision, Recall, and F1-score:** Defined using standard classification performance equations to evaluate sentiment and perception classification effectiveness.
- **Engagement Rate:**

$$\text{Engagement Rate} = \frac{\text{Total Interactions (Likes + Shares + Comments)}}{\text{Total Impressions}} \quad (4)$$

- **Trust Score:** Computed as a weighted average of survey-based Likert scale responses, normalized to a range between 0 and 1.

Discussion

The findings reveal that there is a notable behavioral difference between AI and human influencers. AI-created influencers generate mostly curiosity-based engagements, which make them generate high engagement rates yet low trust scores. However, human influencers create more emotional and credible engagements, thus making their trust score higher. The suggested machine learning algorithm can capture this dual behavioral pattern by combining sentiments and engagements into one evaluation metric.

Implications

This research has several implications for brand marketing. Firms can use AI influencers in awareness-driven marketing campaigns, since engagement rates will be high. At the same time, human influencers will perform better in conversion campaigns because they generate higher trust. Thus, this research enables the development of a data-driven influencer selection strategy.

CONCLUSION

In the current research, a novel hybrid machine learning approach was introduced for assessing consumers' perception of AI-generated influencers relative to human influencers in brand promotion. The framework utilizes sentiment analysis, engagement modeling, and trust evaluation through surveys for developing a quantitative measure of influencer performance in digital marketing environments. Experimental evaluations performed on a data set consisting of 15,000 social media posts and users' engagement show that the hybrid framework can yield a more accurate classification with 96.9% accuracy, compared to other machine learning frameworks, including SVM (88.2%), LSTM (92.5%), and CNN (93.8%). This indicates the effectiveness of the proposed BERT–CNN–Random Forest framework in measuring sentiment and engagement behavior patterns simultaneously. The results of this research indicate a clear behavioral difference between AI-generated and human influencers. Human influencers earn more trust from consumers as they have a mean trust score of 0.81 compared to AI influencers, which display much better engagement performance, with the percentage of likes, shares, and interactions growing 12-18%. This difference between the two types of influencers can also be measured using the calculated Perception Divergence Index (PDI = 0.42). The importance of the conducted research is connected to the creation of a framework for a scalable evaluation of human and AI influences through data and machine learning. Using the model offered by the authors, brands will be able to build marketing strategies based on the chosen type of influence according to the specific goals—high trust or high engagement performance. The limitations of the study include platform dependence and possible sentiment bias of social media posts. In future research, attention needs to be paid to multimodal analysis of influences on visual, audio, and behavioral features of their posts, as well as the development of adaptive and explainable AI models.

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