Performance Prediction and Analysis of YouTube Influencer Marketing Based on Machine Learning

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***Abstract*—With the rapid growth of social media, content creation and sharing have become an integral part of daily life. As the world's largest video platform, YouTube's influence in influencer marketing continues to rise. However, research on predicting the effectiveness of influencer marketing before video publication remains insufficient. Most existing studies rely on early data collected after video publication, which, while accurate, fails to address the need for pre-release predictions and comprehensive multi-metric evaluations. This study employs a machine learning-based multimodal model that integrates pre-publication attributes (such as titles, descriptions, and thumbnails) to classify performance levels (high, medium, low) for metrics like views, comments, and purchase intent. The results demonstrate that the features of target videos significantly contribute to the accuracy of performance predictions. This study provides businesses with a tool to evaluate marketing effectiveness before video release, helping to avoid unnecessary marketing costs.**

***Keywords*—social media, machine learning, influencer marketing, multimodal model, popularity prediction**

I. Introduction

With the rapid development of social media platforms such as Facebook, Twitter, and YouTube, a large amount of media content, including text, images, and videos, is being generated in our daily life. These platforms allow users to create and share content, providing individuals with a stage to express their views and opinions. They have also become important spaces for discussions on political, cultural, and social issues, making them an integral part of our life. The existence of social media platforms has not only fueled the explosive growth of media content but also deepened interactions among people, such as liking, commenting, or viewing, making them a vital component of modern society.

According to the data from "Digital 2023: Global Overview", YouTube is the second most visited website in the world, with approximately 2.5 billion visits per month. Globally, users watch over billions of hours of video content daily, generating hundreds of millions of views (Chi, 2022). As a highly interactive social platform, YouTube's user base continues to grow each year, surpassing 2.6 billion by 2023. Correspondingly, the number of content creators has also surged significantly, increasing by 23% from 2019 to 2020, reaching 38 million (Bärtl, 2018). With its remarkable reach, YouTube offers tremendous advantages for businesses, whether in video content creation or advertising, demonstrating high cost-effectiveness and exposure.

Social Media Influencers (SMIs) were first defined by Freberg *et al.* (2011) as a new type of independent third-party endorsers. These influencers leverage various social media platforms, such as YouTube, Instagram, and blogs, to influence the attitudes and behaviors of their audiences. Under the framework of the S-O-R theory, the content published by social media influencers affects the audience's cognition and emotions, thereby altering their interaction behaviors and purchase decisions. In 2023, it was estimated that 4.9 billion people worldwide use social media, with this number expected to grow to approximately 5.85 billion by 2027. Due to the widespread popularity of social media and the emergence of new business opportunities, billions of users spend significant amounts of time on these platforms, making influencers a powerful tool for reaching a broader audience. With the rapid growth of social media, related terms like "internet celebrities," "key opinion leaders," and "sponsored content" have emerged, giving rise to Influencer Marketing. *Influencer Marketing*, a strategy that involves collaborating with SMIs, has become a popular approach for promoting products and services.

On the YouTube platform, influencer marketing involves collaboration between YouTube influencers (also known as YouTubers) and brands or businesses, a partnership often referred to as "sponsored content". In this type of collaboration, influencers incorporate product mentions, purchase links, and specific hashtags into their videos to increase viewers' purchase intent and enhance the brand's exposure and engagement on social media.

Social media influencers often encourage their fans to engage with them on these platforms. The effectiveness of such interactions can be measured using metrics such as the number of subscribers, views, comments, likes, and shares, which can be leveraged to optimize and select suitable influencers (Leung *et al.*, 2022). As businesses allocate increasing budgets to influencer marketing, the substantial opportunities in this field have attracted millions of new influencers, making the selection of the right influencer increasingly challenging (Pinto *et al.*, 2013). During the selection process, businesses need to consider multiple factors, such as the influencer's audience demographics, content style, and overall compatibility with the promoted product.

Previous studies have often used view count as a metric to evaluate the effectiveness of sponsored YouTube videos (Halim *et al.*, 2022; Jha & Ray, 2023; Pinto *et al.*, 2013). However, the view count cannot truly reflect the effectiveness of sponsorships. Even if a video has a high number of views, it does not necessarily mean that the audience likes the sponsored product featured in the video. On the YouTube platform, comments serve as the best

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feedback mechanism for audiences (Shi *et al.*, 2023), allowing users to express their opinions on various aspects, including the video content, the sponsored product, and the influencer themselves. Therefore, this study argues that analyzing responses to "sponsored products" in video comments, combined with other data sources (e.g., view counts and number of comments), provides a more comprehensive reflection of the true effectiveness of sponsorships.

II. Motivation and Purpose

In the digital era, YouTube, as the world's largest video-sharing platform, serves as a crucial tool for businesses and creators to promote their brands. The popularity of a video directly impacts audience engagement and brand effectiveness, making it essential to predict its marketing performance before publication. Addressing this issue, this study proposes a predictive model that integrates pre-publication attributes, helping businesses formulate more effective marketing strategies.

Previous studies often use the popularity of YouTube videos as the primary indicator to evaluate their effectiveness. Metrics such as view counts, likes, comments, and shares have been analyzed to predict and assess a video's influence (Ahmed *et al.*, 2013). However, while post-publication data is accurate, adjustments made after poor performance are limited in their impact. Therefore, accurately predicting performance before a video's release holds greater practical value.

This study categorizes pre-publication attributes into three main types: influencer characteristics, historical data, and target video attributes. Using a machine learning model, these attributes are integrated to predict a video's marketing performance, including view counts, comment counts, and purchase intent ratios. Unlike previous studies that rely solely on single metrics, this model provides a more comprehensive marketing prediction. Additionally, the study highlights that view counts and purchase intent are not necessarily positively correlated. Audience appreciation for a video's content does not always equate to interest in the sponsored product. Significant differences exist among audiences of various influencers; some influencers may achieve high view counts, yet their fans exhibit lower trust and purchase intent toward promoted products. Therefore, businesses should consider multiple metrics when selecting collaboration partners, rather than relying solely on view counts.

The purpose of this study is to provide an accurate predictive tool before video publication, helping businesses select suitable collaboration partners and maximize the effectiveness of their marketing strategies. This model not only predicts a video's popularity but also evaluates the actual performance of influencer marketing, offering a scientific basis for business decision-making.

III. Literature Reviews

Table 1 summarizes previous studies on YouTube video features and metrics, which used various methods to analyze and predict video popularity. While past research examined pre-publication attributes (e.g., titles, thumbnails) and post-publication engagement data (e.g., views, likes), studies focusing solely on pre-publication attributes are limited. For example, Chen and Chang (2019) proposed a model using pre-publication data to predict the popularity of music videos, selecting variables such as related videos, creators, and keywords, and integrating them with an ensemble classification model. However, their study was limited to the music category and did not account for sponsored video metrics like purchase intent ratios. In contrast, our model addresses these limitations by using a broader dataset across various influencer types and video categories, enabling more accurate predictions of video popularity, and incorporating effectiveness measures for sponsored content.

Table 1. Related studies on YouTube video features and performance metrics

Attribute Availability Time	Before										After					Performance Metrics		
Feature	Video Title	Video Tages	Content Description	Video Length	Thumbnail	Publication Time	Video Category	Subscriber Count	Historical Videos	Popularity of Similar Style Videos	Time Series	Trend Days	View Count	Comment Count	Like Count	View Count	High, Medium, and Low Popularity (View Count Clustering)	Like Count/ View Count
Pinto *et al.* (2013)							V				V		V	V		V		
Roy *et al.* (2013)	V	V					V				V		V			V		
Chen and Chang (2019)	V	V	V					V	V								V	
Tafesse (2020)	V	V	V			V	V	V				V				V		
Batta *et al.* (2022)								V					V	V	V			V
Halim *et al.* (2022)	V	V	V	V	V								V	V	V	V		
Manikandan *et al.* (2022)	V	V	V	V	V	V	V						V	V	V	V		
Jha and Ray (2023)	V		V										V		V	V		

IV. METHOD

A. Problem Definition

In today's digital era, predicting the popularity of online content is crucial for marketers, influencers, and platform operators. Previous research has primarily focused on performance prediction after a video is published, relying on metrics such as view counts and comments (Chi, 2022; Chen & Chang, 2019). However, these approaches often struggle to provide accurate predictions before a video is released. This study aims to utilize various attributes available before the publication of YouTube videos to predict the stable performance metrics of sponsored content, including views, comment counts, and purchase intent ratios.

B. Model Architecture and Methodology

The framework of this study, as illustrated in Fig. 1, combines textual, visual, and numerical features to improve prediction accuracy and stability through a multimodal machine learning model. The model primarily leverages attributes available prior to a video's publication, which are categorized into three main groups based on their nature: influencer attributes (such as subscriber count, number of videos, popularity of similar style videos, and channel name), historical information attributes (such as historical view counts and comment counts), and target video attributes (such as video title, content description, thumbnail, video category, video tags, video length, and publication time).

Textual features are processed using the BERT model, which transforms video titles and descriptions into 768-dimensional vectors. Visual features are extracted using the ResNet-50 model, where each thumbnail image is resized to 224×224 pixels and converted into 1000-dimensional vectors. Numerical features include the average view count of the influencer's last three videos as the historical view count and the number of comments on the last three videos as the historical comment count, reflecting the influencer's recent overall performance. Additionally, the cosine similarity between past video vectors and the target video vector is calculated, and a weighted sum is used to create the "popularity of similar style videos" attribute. Categorical features are encoded into numerical form using One-Hot Encoding, which encodes the video category. Temporal features divide a day into four time periods—early morning, morning, afternoon, and evening—and distinguish between weekdays and weekends to capture the impact of publication timing on performance.

Finally, all features are combined to form an integrated feature vector, which is fed into a multimodal machine learning model for training and prediction.

C. Prediction Model and Classification

This study selects three target variables to evaluate the marketing performance of videos: view count, comment count, and purchase intent ratio. These variables are discretized into three categories—high, medium, and low—using equal-frequency discretization to ensure balance among the categories and to avoid the problem of data imbalance.

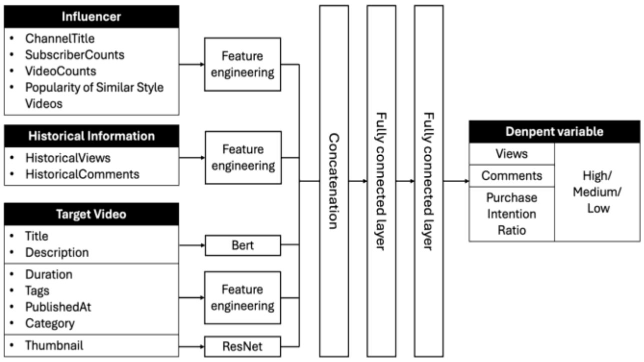

Fig. 1. Conceptual framework.

V. RESULT AND ANALYSIS

A. Data Collection

This study collected all videos by influencers on YouTube that had been published for at least 7 days between November 2022 and December 2023 using the YouTube API. Based on databases provided by NoxInfluencer (a renowned influencer marketing platform), Social Temperature (a leading social media analytics platform in Taiwan), and KOL Radar (a prominent influencer matchmaking platform in Taiwan), an initial list of 149 Taiwanese YouTubers was compiled. From this list, 72 influencers meeting the following criteria were selected. Firstly, the influencers published at least 20 videos annually; Secondly, the videos had not ceased publishing for more than 3 months; The last, the videos released at least 5 sponsored per year. Ultimately, 9,340 videos were collected, and 12 attributes were recorded, including channel name, publication time, title, description, category, tags, thumbnail, and others.

To filter sponsored videos, this study established four judgment criteria. A video was classified as sponsored if it met at least one of the following conditions: 1. The video explicitly mentioned a brand or product name (a mandatory condition); 2. The description included a link to purchase a product; 3. A product discount code was provided; 4. The title or description contained brand-related hashtags, such as "feat," or @mentions. This filtering method ensured that the videos in the dataset possessed characteristics of sponsored content, thereby supporting the research analysis.

B. Experimental Setup

This study utilized data from 8,411 videos published by 72 influencers, including 1,783 sponsored videos. To prevent data leakage, the dataset was partitioned chronologically. For the prediction of view count and comment count, data from January to November were used as the training set, while data from December were used as the testing set. For the purchase intent ratio model, which focused exclusively on sponsored videos, data from January to October were used as the training set, and data from November to December were used as the testing set to ensure enough test samples.

The model training process utilized the Adam optimizer with a learning rate of 1e-4 and employed the cross-entropy loss function to handle classification tasks. Each training iteration consisted of 30 epochs with a batch size of 100, and dropout layers were incorporated to prevent overfitting. After determining the optimal hyperparameter combination through 10-fold cross-validation, the model was retrained on the entire training set. Finally, the model's performance was evaluated on an independent test set to ensure its accuracy and stability on unseen data.

C. Experimental Result

The experimental results of this study are presented in Table 2, where the performance of three different models—view count, comment count, and purchase intent ratio—was evaluated. First, the view count model achieved an accuracy of 65.77%, demonstrating high precision and a strong F1 score in the low view count category. This indicates that the model has robust predictive capability for samples with low view counts.

Secondly, the comment count model achieved an accuracy of 72.14%, exhibiting high precision and a strong F1 score in the low comment count category, indicating robust predictive capability for this category. Additionally, the model demonstrated balanced performance across the medium and high comment count categories.

Finally, the purchase intent ratio model achieved an accuracy of 66.87%, with outstanding performance in the low purchase intent ratio category, achieving the highest precision and F1 score.

D. Ablation study

In this section, an ablation study was conducted on the three influencer marketing performance indicators—view count, comment count, and purchase intent ratio—to investigate the contribution of three major feature categories: target video, influencer, and historical information features, to the performance of different sponsored content. The results of the ablation study are summarized in Table 3.

The experimental results of the view count prediction model indicate that when all features are included, the model achieves an accuracy of 65.48% (Model 1). However, after removing the video features, the accuracy drops significantly to 57.14% (Model 2), demonstrating that target video features are essential and indispensable for the model's accuracy.

According to the experimental results of the comment count prediction model, the model achieves an accuracy of 72.14% (Model 1) when all features are included. However, after removing the target video features, the accuracy drops significantly to 57.57% (Model 2), highlighting the critical role of video features in comment count prediction as well.

With the complete feature set, the purchase intent prediction model achieves an accuracy of 66.87% (Model 1). However, after removing the target video features, the accuracy drops significantly to 60.89% (Model 2), indicating that the feature is crucial to the model's performance.

VI. Conclusion

A. Summary of Results

This study aims to leverage machine learning techniques to predict the effectiveness of YouTube influencer marketing performance, addressing the challenges businesses face in selecting suitable influencers and evaluating sponsored content performance. As the study focuses on analyzing the performance of sponsored videos, we introduced the purchase intent ratio variable, derived from analyzing audience feedback in comments to provide a more authentic indicator of sponsored content effectiveness. This new metric not only enriches the evaluation methods for sponsored content performance but also extends the consideration of influencers' long-term characteristics.

The experimental results demonstrate that appropriately incorporating target video, influencer, and historical information features enhances the accuracy of the prediction model. Additionally, the newly introduced purchase intent ratio variable, combined with audience comment feedback, provides a more authentic and comprehensive metric for evaluating the effectiveness of sponsored content.

Table 2. Experimental result

DV	**Views**			**Comments**			**Purchase Intention Ratio**		
Accuracy	65.77%			72.14%			66.87%		
Metric	**High**	**Medium**	**Low**	**High**	**Medium**	**Low**	**High**	**Medium**	**Low**
Precision	0.50	0.57	0.87	0.69	0.65	0.79	0.59	0.54	0.88
Recall	0.79	0.56	0.67	0.80	0.62	0.75	0.66	0.57	0.76
F1-score	0.61	0.56	0.76	0.74	0.64	0.77	0.62	0.55	0.81

Table 3. Ablation study

Ablation study	Model Features Used					Advertorial Performance (Acc.)		
	Target video	Influencer		Historical Information		View Counts	Comment Counts	Purchase Intent Ratio
		Influencer (Excluding the Popularity of Similar Style Videos)	Popularity of Similar Style Videos	Historical Views Count	Historical Comments Count			
Model 1	V	V	V	V	V	65.48%	72.14%	66.87%
Model 2		V	V	V	V	57.14%	57.28%	60.89%

【Annotation】
Model 1: The model using all features for prediction.
Model 2: Removed target video features.

B. Limitations and Future Research

This study analyzed data from YouTube influencers and their sponsored videos. While these data reflect market trends, their applicability to other regions or cultural contexts remains to be validated. Although pre-publication attributes can effectively predict performance, the lack of actual audience behavior data may limit the accuracy of the predictions, particularly regarding purchase intent. Furthermore, the model's data source relies on public APIs, which may be constrained by the completeness and update frequency of the data.

For future research, it is recommended to expand the data scope by including other social media platforms to further test the model's generalizability and performance. Additionally, incorporating more variables that influence performance, such as audience characteristics, could address the limitations of pre-publication attributes. Moreover, integrating initial post-publication data, such as view count, click-through rate, and interaction metrics, with pre-publication attributes for a combined analysis could enhance the accuracy of the model.

Finally, the practical application of the model can focus on assisting businesses in selecting suitable influencers and adjusting marketing strategies. Future developments could include creating more intuitive data visualization tools to help businesses quickly interpret the model's predictions, thereby further enhancing the efficiency of resource utilization in influencer marketing.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Yi-Syuan Huang and Yu-Hsuan Chou wrote the main manuscript text; Chia-Chi Wu proposed the research questions; Ai-Wei Liu and Chia-Chi Wu developed the conceptual framework; Yi-Syuan Huang, Yu-Hsuan Chou, and Ai-Wei Liu conducted the experiments; all authors had approved the final version.

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