AI-DRIVEN SOCIAL MEDIA INFLUENCER ANALYTICS: A COMPREHENSIVE REVIEW OF IDENTIFICATION, CLASSIFICATION, AND MARKETING APPLICATIONS

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Abstract : Social media influencers have become important intermediaries in digital communication, online marketing, education, healthcare, fitness, and electronic commerce. However, the rapid expansion of influencer-driven content has made the manual identification, classification, and evaluation of suitable influencers increasingly complex, subjective, and time-consuming. Artificial intelligence (AI) provides data-driven techniques for analysing influencer profiles, content characteristics, audience behaviour, network relationships, engagement patterns, credibility, and marketing performance. This paper presents a comprehensive review of AI-driven social media influencer analytics, focusing on influencer identification, classification, and marketing applications. It examines conventional machine learning, deep learning, natural language processing, transformer-based, graph-based, ensemble, and multimodal approaches used in existing studies. The review further analyses commonly employed profile, content, engagement, sentiment, visual, and network features, along with datasets, social media platforms, and performance evaluation metrics. A comparative analysis is conducted to identify the advantages, limitations, and application suitability of different AI techniques. The findings indicate that transformer-based and graph-based approaches offer strong capabilities for contextual content analysis and network-aware influencer identification, whereas ensemble and multimodal models provide improved robustness by integrating heterogeneous information. Nevertheless, the field remains constrained by limited benchmark datasets, platform-dependent models, fake engagement, insufficient explainability, privacy concerns, and algorithmic bias. Finally, the paper identifies future research opportunities involving explainable AI, graph neural networks, multimodal transformers, cross-platform learning, real-time analytics, and ethical influencer recommendation systems.

IndexTerms – Artificial intelligence, social media influencers, influencer analytics, influencer identification, influencer classification, influencer marketing, machine learning, natural language processing, graph-based learning, multimodal analysis.

INTRODUCTION

Social media influencers have become important intermediaries in digital marketing, education, healthcare, entertainment, and electronic commerce. Through their content and interactions, influencers can affect consumer behaviour, brand perception, public opinion, and technology adoption. Influencer marketing has consequently developed into a significant research area involving audience engagement, content strategy, influencer selection, and campaign performance. Existing review research has summarized its theoretical foundations, major trends, and future research opportunities [2]. The influence of social media creators has also extended to education, where reviews have examined how AI-focused educational influencers shape the discussion and adoption of emerging technologies in schools [1].

Identifying suitable influencers is challenging because social influence cannot be determined solely from follower counts. It is affected by engagement, credibility, content relevance, network position, audience characteristics, and information-diffusion capability. Previous systematic reviews have classified influencer-identification techniques according to their datasets, influence measures, network properties, and computational approaches [3]. Related survey research has further examined social media influence environments, influencer characteristics, and identification methods [4]. These studies reveal substantial variation in how influence is defined, measured, and evaluated across social media platforms.

Artificial intelligence enables the automated analysis of large-scale textual, visual, behavioural, and network data. Machine learning, deep learning, natural language processing, transformer models, graph-based learning, and ensemble methods have been applied to influencer identification, profile classification, fake-account detection, engagement prediction, and influencer–brand matching. However, algorithmic influencer-management systems may introduce concerns related to transparency, brand safety, privacy, and bias in influencer ranking and selection [5]. Therefore, AI-driven influencer analytics must consider responsible and explainable decision-making alongside predictive performance.

Although existing reviews examine influencer marketing, influencer identification, influence environments, educational influencers, and algorithmic management tools, these areas are generally addressed independently. Therefore, this paper presents a comprehensive review of AI-driven social media influencer analytics by integrating three major areas: influencer identification, influencer classification, and marketing applications. It compares the AI techniques, features, datasets, platforms, evaluation metrics, and applications reported in existing studies and identifies research challenges involving benchmark datasets, cross-platform generalization, fake engagement, explainability, privacy, fairness, and multimodal analytics.

II. BACKGROUND AND CONCEPTUAL FOUNDATIONS

Social Media Influencers and Influence

Social media influencers are individuals or virtual entities capable of affecting audience opinions, behaviours, and purchasing decisions through their expertise, credibility, content, or network position. They are commonly categorized as nano-, micro-, macro-, and mega-influencers according to their audience size. However, follower count alone does not accurately represent influence, as smaller influencers may achieve stronger audience trust and engagement. Therefore, content relevance, credibility, authenticity, engagement rate, audience quality, and information-diffusion capability should also be considered when measuring social influence [2]–[4].

Influencer Analytics Tasks

Influencer analytics primarily comprises identification, classification, and evaluation. Influencer identification aims to discover users with substantial reach, authority, engagement, or information-diffusion capability. Classification assigns influencers to categories based on audience size, content domain, behavioural characteristics, authenticity, or marketing suitability. Evaluation measures influencer credibility, audience compatibility, engagement quality, and expected campaign performance. These tasks also support fake-profile detection, sponsored-content identification, influencer recommendation, and brand–influencer matching.

Role of Artificial Intelligence

Artificial intelligence enables the automated analysis of large-scale profile, content, engagement, and network data. Machine-learning algorithms process features such as follower count, posting frequency, engagement rate, account activity, and network centrality. Natural language processing and transformer models analyse captions, topics, sentiments, and emotional content, whereas graph-based methods examine user relationships and information-diffusion patterns. Deep-learning and multimodal models further integrate textual, visual, behavioural, and network features to provide more comprehensive influencer assessments. Nevertheless, automated influencer-management systems must address algorithmic bias, transparency, privacy, brand safety, and explainability to ensure responsible influencer ranking and selection [5].

III. RELATED WORK AND REVIEW METHODOLOGY

Existing studies on AI-driven influencer analytics can be broadly categorized into influencer classification, influential-node identification, authenticity detection, audience analysis, and marketing optimization. Transformer-based classification has been applied to Instagram captions, with fine-tuned multilingual BERT achieving approximately 80% accuracy in categorizing influencers [6]. An intelligent marketing platform combining pretrained language models with influencer-performance features reported more than 90% classification accuracy [11]. Multidimensional approaches integrating graph neural networks, topic modelling, sentiment analysis, user behaviour, and community structure have further improved influencer identification and personalized marketing recommendations [13].

Network-based studies identify influential users by examining social relationships and information-diffusion patterns. A hybrid RF–GBDT model incorporating centrality measures, PageRank, and clustering coefficients achieved an accuracy of 96.7% for influential-node identification [10]. Graph-embedding methods such as Node2Vec and Word2Vec have also been employed for link prediction and community detection in Instagram influencer networks [17]. Other approaches combine PageRank, data profiling, and conventional machine-learning algorithms to characterize influential users [24]. Comparative analysis of several classifiers for imbalanced influencer-identification data found Random Forest to be an effective model [27].

AI techniques have additionally been used to evaluate authenticity, sponsored content, and audience responses. Ensemble learning with XGBoost, SMOTE, and Random Forest achieved high performance in detecting fake Instagram profiles [14]. Transformer models have been investigated for distinguishing sponsored and non-sponsored posts [22], while large-scale Instagram analysis has demonstrated the ability of machine-learning models to detect undisclosed sponsored content [29]. NLP, BERT, and deep-learning models have also been used to identify emotional responses to influencers' mental-health content, with BERT-based models producing accuracies between 86% and 90% [18].

Influencer analytics has several domain-specific marketing applications. Existing studies have examined educational influencers and their professional, ethical, and commercial roles [7], [12], [15], [26]; human and virtual influencer authenticity and engagement [9], [21]; influencer success factors [19]; fitness-influencer competency evaluation [20]; and engagement with sponsored posts [25]. Other approaches combine amplification, content creation, and brand relevance for campaign-specific influencer selection [23] or optimize influencer selection and message scheduling for short- and long-term campaigns [28].

For this review, relevant studies were organized according to three principal dimensions: influencer identification, influencer classification, and marketing applications. Each study was compared using its social media platform or dataset, input features, AI methodology, application, evaluation measures, principal findings, and reported limitations. This thematic organization enables a structured comparison of existing approaches and supports the identification of methodological limitations and future research directions.

IV. FEATURES, DATASETS, AND MARKETING APPLICATIONS

The performance of AI-driven influencer analytics depends on the quality of the collected data and the relevance of the extracted features. Existing studies generally employ profile, behavioural, content, engagement, and network features obtained from social media platforms. These features are processed individually or combined to support influencer identification, classification, credibility assessment, and marketing-related decisions.

Profile and Behavioural Features

Profile features describe the general characteristics of an influencer account, including follower and following counts, account age, verification status, posting frequency, content category, and audience growth. Behavioural features represent how consistently influencers create content and interact with their audiences. Engagement-related variables, such as likes, comments, shares, views, and engagement rate, are also widely used to estimate audience responsiveness. Large-scale analysis of social media posts has shown that influencer type, appearance, persuasive communication, and content-processing strategies can affect user engagement [19]. Engagement also varies according to influencer size, sponsorship status, and the type of advertising appeal used in posts [25].

Content and Semantic Features

Content features are extracted from captions, hashtags, comments, images, and videos published by influencers. Conventional text representations include term frequency–inverse document frequency, n-grams, and word embeddings, whereas recent studies employ contextual representations obtained from pretrained transformer models. Fine-tuned multilingual BERT has been used to classify Instagram influencers based on caption content [6]. Similarly, pretrained language models combined with performance-related features have supported influencer categorization and advertisement matching [11].

Semantic features include topics, sentiments, emotions, content relevance, and brand-related expressions. A multidimensional approach integrating topic modelling, sentiment analysis, user behaviour, and community information demonstrated the importance of combining structural and semantic influence [13]. BERT and deep-learning models have also been used to analyse emotional responses to influencer-generated mental-health content [18]. Sponsored-content detection further relies on linguistic patterns and contextual relationships between influencers and brands [22], [29].

Network and Structural Features

Social media networks can be represented as graphs in which users are treated as nodes and follows, mentions, comments, shares, or collaborations are represented as edges. Network features measure the structural importance and information-diffusion capability of each influencer. Common measures include degree, betweenness, closeness and eigenvector centralities, PageRank, clustering coefficients, community membership, and interaction density.

A hybrid influencer-identification model combining these topological features with Random Forest and gradient boosting achieved better performance than conventional centrality-based techniques [10]. Graph-embedding approaches, including Node2Vec and Word2Vec, have also been applied to link prediction and community detection in Instagram influencer networks [17]. Other studies have combined PageRank with machine-learning models for influencer profiling [24] or used amplification factors and content-creation scores to identify influential users for marketing campaigns [23].

Datasets and Social Media Platforms

Existing influencer-analytics studies predominantly use platform-specific datasets collected from Instagram, Twitter/X, Facebook, Sina Weibo, and Xiaohongshu. Instagram is widely studied because it provides profile, caption, visual, engagement, and sponsorship information. It has been used for influencer classification [6], fake-profile detection [14], human–virtual influencer comparison [9], [21], educational-influencer analysis [7], [26], and sponsored-content analysis [25], [29].

Twitter/X datasets have been used to evaluate influencer effects on academic visibility [16], classify sponsored posts [22], and optimize influencer selection and campaign scheduling [28]. Facebook data have supported influencer detection using amplification and content-creation factors [23], while Sina Weibo data have been analysed through graph neural networks, sentiment analysis, and multidimensional feature fusion [13]. Xiaohongshu has also been used to investigate the content, motivations, and professional experiences of educational influencers [15].

Most datasets are privately collected through platform APIs, web-based data collection, questionnaires, or manual annotation. As a result, they vary considerably in size, feature definitions, influencer categories, and labelling procedures. Limited access to standardized public datasets makes direct model comparison difficult. Dataset imbalance is another important issue because influential, fraudulent, or sponsored accounts may represent only a small proportion of the collected users [14], [27].

Marketing and Domain-Specific Applications

AI-driven influencer analytics supports influencer identification, ranking, classification, brand matching, campaign optimization, engagement prediction, and authenticity assessment. Intelligent marketing platforms can classify influencers and recommend suitable advertising partnerships by combining textual information with performance features [11]. Data-driven optimization models can also select influencers and schedule their posts for short- and long-term marketing campaigns [28]. The effectiveness of these systems depends on audience relevance, influencer credibility, interaction frequency, content quality, and expected campaign reach.

AI methods are also used to detect fake profiles [14], identify sponsored content [22], [29], analyse emotional audience responses [18], and assess influencer competency [20]. Comparisons between human and virtual influencers examine perceived authenticity, trust, engagement, and purchase intention [9], [21]. Beyond commercial marketing, influencer analytics supports educational outreach and community-awareness programs [7], [12], [15], [26]. These diverse applications demonstrate that effective influencer selection requires the combined analysis of profile, content, engagement, and network information rather than dependence on a single popularity measure.

V. AI-BASED INFLUENCER IDENTIFICATION AND CLASSIFICATION

AI-driven influencer analytics transforms heterogeneous social media data into meaningful influencer categories, rankings, credibility scores, and marketing recommendations. Existing approaches range from conventional machine-learning classifiers to transformer-based language models, graph learning, ensemble methods, and multidimensional feature-fusion techniques. The selection of an appropriate model depends on the available data, analytical objective, computational resources, and expected output.

AI-Driven Influencer Analytics Framework

The proposed generic framework, shown in Figure 1, begins with the collection of profile, textual, visual, engagement, and network data from social media platforms

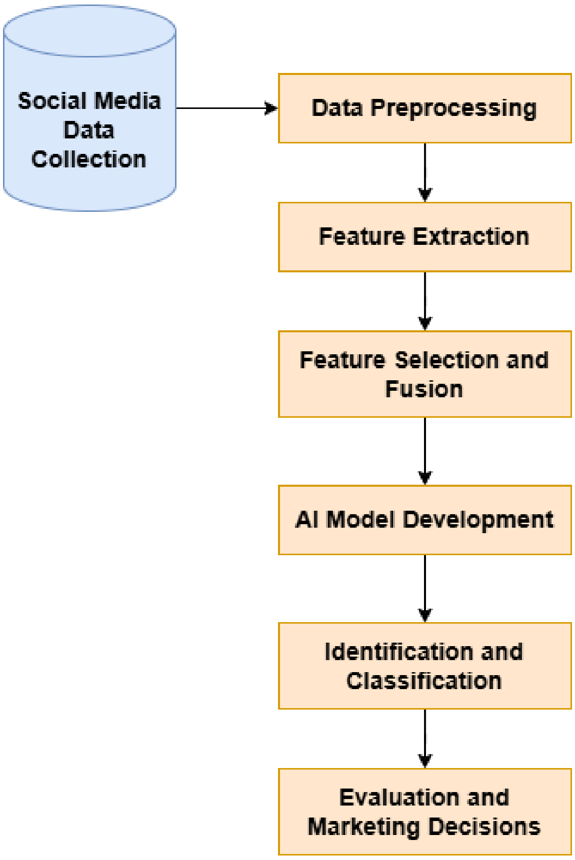

Figure 1: AI-Driven Influencer Analytics Framework

The collected data are preprocessed by removing duplicate records, missing values, URLs, irrelevant symbols, and noisy interactions. Textual content is normalized and tokenized, numerical features are scaled, and class-balancing techniques are applied when the number of influencer and non-influencer accounts is unequal. Stop-word handling and hyperparameter selection can significantly affect transformer-based influencer classification [6], whereas SMOTE and class-weight optimization have been used to improve fake-profile detection [14].

Feature extraction generates profile, behavioural, semantic, engagement, and network representations. These features may be selected to remove irrelevant or redundant variables and then fused into a unified representation. The resulting feature set is provided to an AI model for influencer identification, classification, credibility estimation, or marketing recommendation. The final output can include influential-user rankings, influencer categories, fake-profile labels, sponsored-content labels, and influencer–brand compatibility scores.

A. Conventional Machine-Learning Models

Conventional machine-learning models are suitable when social media data are represented through structured and handcrafted features. Common algorithms include logistic regression, K-nearest neighbours, support vector machines, decision trees, Random Forest, gradient boosting, and XGBoost. These models use variables such as follower count, engagement rate, posting frequency, account age, content category, and centrality measures.

Comparative analysis of machine-learning methods for imbalanced influencer-identification data found Random Forest to be an effective classification method [27]. PageRank has also been combined with machine-learning models to profile influential nodes in social networks [24]. For fake-profile detection, an optimized ensemble incorporating Random Forest, XGBoost, SMOTE, and hyperparameter tuning achieved high accuracy, precision, recall, and F1-score [14]. Although conventional models are computationally efficient and relatively interpretable, their performance depends strongly on feature engineering and data quality.

B. NLP and Transformer-Based Models

NLP models analyse captions, comments, hashtags, sentiments, emotions, topics, and brand-related expressions. Conventional NLP techniques employ term frequency, TF–IDF, sentiment lexicons, and topic modelling. Transformer models such as BERT generate contextual representations that capture relationships between words more effectively than conventional text representations.

Fine-tuned multilingual BERT has been applied to classify Instagram influencers from their captions, achieving approximately 80% accuracy [6]. Pretrained language models combined with influencer-performance features have produced classification accuracy exceeding 90% in an intelligent marketing platform [11]. BERT-based models have also achieved strong results in identifying emotional reactions to mental-health content [18]. Furthermore, BERT, GPT-2, and GPT-Neo have been investigated for detecting sponsored influencer posts [22]. However, transformer models require considerable training resources and may provide limited interpretability.

C. Graph-Based and Hybrid Models

Graph-based approaches represent influencers as nodes and social interactions as edges. Influential users are identified using centrality measures, community structure, graph embeddings, and information-diffusion characteristics. Traditional graph methods employ degree, betweenness, closeness and eigenvector centralities, PageRank, and clustering coefficients.

A hybrid RF–GBDT model combining machine learning with topological network features achieved 96.7% accuracy for influential-node identification [10]. Node2Vec and Word2Vec embeddings have been used to analyse influencer relationships, conduct link prediction, and identify online communities [17]. More advanced multidimensional models integrate graph neural networks, content semantics, topic modelling, sentiment orientation, and user behaviour to improve influencer identification and personalized marketing [13]. These hybrid approaches provide a more comprehensive assessment because social influence depends on both network position and content relevance.

D. Identification and Classification Outputs

Influencer identification models determine whether a user is influential or generate a ranked list of influential accounts. Classification models assign influencers to categories according to audience size, content domain, authenticity, competency, or marketing suitability. Influencers may be categorized as nano-, micro-, macro-, or mega-influencers or classified into domains such as education, healthcare, fitness, fashion, and technology.

Other classification outputs include human versus virtual influencers [9], [21], genuine versus fake profiles [14], and sponsored versus non-sponsored content [22], [29]. Marketing-oriented models can recommend suitable influencers, predict engagement, evaluate campaign performance, and optimize influencer selection and post scheduling [11], [28]. These outputs enable marketers to move beyond follower-based selection and adopt more reliable data-driven decisions.

E. Performance Evaluation

Influencer-classification models are commonly evaluated using accuracy, precision, recall, F1-score, and ROC–AUC. Precision represents the proportion of predicted influencers that are relevant, whereas recall measures the proportion of actual influencers correctly identified. The F1-score balances precision and recall and is particularly useful for imbalanced datasets. Ranking and recommendation systems may additionally use precision at K, recall at K, mean average precision, and normalized discounted cumulative gain. Computational time, scalability, interpretability, and cross-platform performance should also be evaluated to determine whether a model is appropriate for real-world influencer analytics.

VI. COMPARATIVE ANALYSIS AND DISCUSSION

Existing studies demonstrate that AI-driven influencer analytics employs diverse data sources, features, models, and evaluation strategies. Some approaches focus on identifying structurally important users, while others classify influencers, detect fraudulent accounts, analyse audience responses, or optimize marketing campaigns. Table I compares representative AI-based approaches according to their data, methodology, application, performance, and limitations.

Table I: Comparative Analysis of AI-Driven Influencer Analytics

Ref.	Platform/Data	Methodology	Application	Result Evaluation	Limitation
[6]	Instagram captions	Fine-tuned multilingual BERT	Influencer classification	Accuracy: 80%	Limited to caption-based Indonesian Instagram data
[10]	Simulated social network	Centrality features with RF–GBDT	Influential-node identification	Accuracy: 96.7%	Limited validation on real-world networks
[11]	SNS post-text dataset	Pretrained language model with performance features	Classification and advertisement matching	Accuracy: >90%	Dataset and platform dependence
[13]	Sina Weibo, 8,000 bloggers	GNN, topic modelling, sentiment analysis and feature fusion	Identification and personalized marketing	Sentiment accuracy: 92.3%; top-50 F1: 0.88	High model and data complexity
[14]	Instagram profiles	XGBoost, Random Forest, SMOTE and GridSearchCV	Fake-profile detection	Accuracy: 98.24%; F1: 98%	Generalization across platforms is uncertain
[17]	Instagram network	Node2Vec and Word2Vec	Link prediction and community detection	Network patterns identified	Limited content and semantic analysis
[18]	Instagram mental-	RF, deep learning and BERT	Emotional-response	BERT accuracy: 86–	Emotion labels can be

Ref.	Platform/Data	Methodology	Application	Result Evaluation	Limitation
	health content		classification	90%	subjective
[22]	Influencer tweets	BERT, GPT-2 and GPT-Neo	Sponsored-post classification	Comparative model evaluation	Focused mainly on textual information
[23]	Facebook campaign data	Amplification factors and content-creation scores	Campaign-specific influencer detection	Improved conversion and revenue	Application-specific feature design
[24]	Social network profiles	PageRank and machine learning	Influencer profiling	Significant feature correlations	Performance metrics are not consistently reported
[27]	Social media user data	LR, LDA, KNN, SVM and tree-based models	Influencer identification	Random Forest selected as the best model	Imbalanced and platform-specific data
[28]	Twitter campaign data	Data-driven mathematical optimization	Influencer selection and scheduling	Improved short- and long-term planning	Requires campaign-specific parameters
[29]	Large-scale Instagram data	Machine-learning classifiers	Sponsored-content detection	Sponsored and unlabelled posts detected	Dependent on advertisement labelling quality

A. Comparison of AI Approaches

Conventional machine-learning models provide comparatively low computational complexity, faster training, and greater interpretability. Random Forest, SVM, gradient boosting, and XGBoost perform effectively when profile, behavioural, engagement, and network features are available in structured form [10], [14], [27]. However, their performance depends heavily on manually engineered features and may decrease when applied to unstructured text, images, or videos.

Transformer-based approaches offer stronger contextual understanding of influencer-generated content. Fine-tuned BERT has demonstrated its effectiveness in influencer classification [6], intelligent advertising matching [11], and emotional-response analysis [18]. Transformer models can distinguish subtle linguistic and semantic differences that conventional feature representations may overlook. Nevertheless, they require considerable computational resources, large labelled datasets, and careful hyperparameter selection. Caption-only models may also fail to capture network position, visual quality, and audience authenticity.

Graph-based models are particularly suitable for influential-node identification because they represent relationships, communities, and information-diffusion processes. Centrality-based machine learning [10], graph embeddings [17], and graph neural networks [13] provide network-aware measures of influence. However, these methods require reliable relationship data and may face scalability difficulties in large and dynamic social networks. Their performance may also be affected by incomplete connections, private accounts, platform restrictions, and manipulated interactions.

Hybrid and multidimensional models generally provide more comprehensive influencer evaluations. Combining structural, semantic, behavioural, and engagement features improves the ability to capture different dimensions of influence [11], [13]. Ensemble learning can also increase robustness and improve the detection of fake accounts [14]. The main disadvantages of hybrid approaches are higher computational complexity, reduced interpretability, and difficulties in determining the contribution of individual feature groups.

B. Major Findings

The comparative analysis produces the following observations:

No single feature represents influence completely. Follower counts and engagement rates are useful but should be combined with content quality, audience relevance, authenticity, and network position.

Traditional machine learning remains effective for structured data. Random Forest, gradient boosting, and XGBoost provide strong performance for profile-based classification, influential-node identification, and fake-account detection [10], [14], [27].

Transformer models are more suitable for content-oriented tasks. BERT-based models perform well in caption classification, sentiment and emotion analysis, and sponsored-content detection [6], [18], [22].

Graph-based models capture relational influence. Centrality measures, graph embeddings, and GNNs are effective when user connections and information-diffusion patterns are important [10], [13], [17].

Feature fusion improves analytical coverage. Combining profile, content, engagement, and network features produces more comprehensive influencer representations than using a single data source [11], [13].

AI applications extend beyond commercial marketing. The reviewed methods also support educational outreach, mental-health communication, fitness evaluation, academic visibility, and community programmes [7], [12], [16], [18], [20], [26].

C. Critical Discussion

Although several studies report high classification performance, their numerical results cannot be compared directly because they use different platforms, datasets, class definitions, features, sampling procedures, and evaluation protocols. For example, the high performance reported for fake-profile detection [14] does not imply that the same model would outperform transformer or graph-based models in influencer-category classification. Each result must therefore be interpreted within its specific task and dataset.
Most studies rely on privately collected or platform-specific datasets, limiting reproducibility and cross-platform generalization. Instagram dominates the reviewed literature, while comparatively fewer studies examine TikTok, YouTube, or integrated cross-platform datasets. In addition, static datasets may not adequately represent changes in influencer popularity, audience behaviour, and platform algorithms over time.
The literature also emphasizes predictive performance more frequently than transparency, fairness, privacy, and practical deployment. Few studies explain why a particular influencer receives a high score or recommendation. Future comparative evaluations should therefore consider not only accuracy and F1-score but also model interpretability, computational cost, robustness to fake engagement, scalability, temporal stability, and transferability across platforms.

VII. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

Despite the progress achieved through machine learning, transformer models, graph analysis, and multimodal learning, AI-driven influencer analytics continues to face challenges related to data availability, model generalization, manipulation, explainability, privacy, and fairness. Addressing these limitations is necessary for developing reliable and practically deployable influencer-analytics systems.

A. Dataset Availability and Standardization

Most existing studies use privately collected and platform-specific datasets with different feature definitions, influencer categories, and annotation procedures [6], [11], [13], [14]. Consequently, the reproducibility and direct comparison of existing models remain limited. Future research should develop publicly available benchmark datasets containing anonymized profile, content, engagement, audience, and network information. Standard train–validation–test partitions and consistent evaluation metrics should also be established to support fair model comparison.

B. Cross-Platform Generalization

Influencer behaviour and audience engagement vary across Instagram, Twitter/X, Facebook, YouTube, TikTok, Sina Weibo, and Xiaohongshu. Models trained using data from one platform may not generalize to another because platforms have different content formats, user communities, interaction mechanisms, and recommendation algorithms. Future studies should investigate transfer learning, domain adaptation, and platform-independent feature representations to develop generalized influencer-identification and classification models.

C. Fake Engagement and Dynamic Influence

Follower counts, likes, comments, and shares can be manipulated through bots, purchased followers, engagement groups, or coordinated activities. Although existing studies have examined fake-profile and undisclosed sponsored-content detection [14], [22], [29], identifying sophisticated manipulation remains challenging. Moreover, social influence changes over time due to trends, audience migration, platform policies, and content popularity. Temporal graph networks and continual-learning models could support the real-time detection of fake engagement and dynamic changes in influencer status.

D. Explainability and Model Transparency

Transformer, ensemble, and graph neural network models may provide high predictive performance but often operate as black-box systems. Marketers and content creators may therefore be unable to determine why an influencer was selected, rejected, or assigned a particular category. Algorithmic influencer-management tools may also introduce bias and unequal visibility [5]. Future research should integrate explainable AI techniques, including SHAP, LIME, attention visualization, and feature-importance analysis, to provide transparent influencer rankings and recommendations.

E. Multimodal and Context-Aware Analytics

Many current studies analyse profile statistics, text, or network structure independently. However, actual influence is produced through the interaction of captions, images, videos, audio, audience reactions, and social relationships. Multidimensional feature fusion has demonstrated the benefits of integrating structural and semantic information [13]. Future systems should employ multimodal transformers and graph neural networks to jointly model textual, visual, behavioural, temporal, and network characteristics. Contextual variables such as content domain, audience demographics, campaign objectives, and cultural background should also be included.

F. Privacy, Fairness, and Ethical Considerations

Influencer analytics may involve the collection of personal profiles, audience interactions, demographic information, and behavioural data. Such data create concerns regarding informed consent, privacy, surveillance, and unauthorized profiling. Educational and community applications further require attention to cultural sensitivity and responsible data use [7], [12]. Future frameworks should adopt privacy-preserving learning, data anonymization, consent-based collection, fairness auditing, and bias-mitigation methods. Sponsored-content disclosure and the ethical use of virtual influencers should also be considered [9], [21].

G. Real-Time and Application-Oriented Systems

Many existing approaches are evaluated using static datasets and offline experiments. Real-world marketing environments require scalable systems capable of processing continuous social media streams, detecting emerging influencers, updating rankings, and responding to changes in audience behaviour. Future studies should develop real-time analytics platforms that integrate influencer identification, classification, brand matching, campaign scheduling, and performance monitoring. Such platforms should balance predictive performance with computational efficiency, explainability, ethical compliance, and marketing relevance.

Overall, future AI-driven influencer analytics should move toward standardized, cross-platform, explainable, multimodal, privacy-preserving, and temporally adaptive models. These developments would improve the reliability of influencer selection and enable more transparent and responsible applications in marketing, education, healthcare, and public communication.

VIII. CONCLUSION

This paper presented a comprehensive review of AI-driven social media influencer analytics, focusing on influencer identification, classification, and marketing applications. The reviewed studies demonstrate that social influence is a multidimensional concept determined by profile characteristics, content relevance, audience engagement, authenticity, network position, and information-diffusion capability. Therefore, follower count alone is insufficient for reliable influencer evaluation and selection.

The comparative analysis showed that traditional machine-learning models, including Random Forest, SVM, gradient boosting, and XGBoost, remain effective for structured profile, behavioural, and network data. Transformer-based models provide stronger contextual analysis of captions, sentiments, emotions, and sponsored content, whereas graph-based methods capture social relationships, community structures, and information diffusion. Hybrid and multidimensional approaches offer more comprehensive evaluations by integrating content, engagement, behavioural, and network features. These AI methods support influencer ranking, profile classification, fake-account detection, sponsored-content identification, brand matching, engagement prediction, and campaign optimization.

Despite encouraging results, existing approaches are limited by privately collected datasets, inconsistent influencer definitions, platform-specific models, fake engagement, limited reproducibility, and inadequate model explainability. Privacy, fairness, algorithmic bias, and responsible use of audience data also require greater attention. Future research should therefore focus on standardized cross-platform datasets, multimodal transformers, graph neural networks, explainable AI, temporal modelling, privacy-preserving analytics, and real-time influencer recommendation systems. These advancements can support more accurate, transparent, and responsible influencer analytics across marketing, education, healthcare, and other social-media applications

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