STRATEGIC MANAGEMENT OF SOCIAL MEDIA INFLUENCE NETWORKS FOR ENHANCED LOCAL GOVERNANCE AND COMMUNITY ENGAGEMENT

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Abstract: Social media has emerged as a critical tool for local governments and public institutions to engage citizens, disseminate information, and shape public opinion. This study proposes a graph analytics approach to quantify influence and optimize communication strategies within social networks, emphasizing local governance and community engagement. By employing network centrality metrics such as degree, betweenness, closeness, and eigenvector centrality, the research identifies key opinion leaders and influential nodes that significantly impact information diffusion and citizen engagement. The proposed model enables local authorities to prioritize communication efforts, enhance public outreach, and improve policy dissemination. Empirical validation using datasets from municipal social media platforms demonstrates that targeted engagement strategies informed by network analytics lead to higher interaction rates, increased citizen participation, and more effective community-focused campaigns. The findings highlight the potential of data-driven social media strategies to strengthen local governance, enhance transparency, and foster participatory democracy.

Keywords: Social Media, Graph Analytics, Influencer Score, Network Centrality, Marketing Strategy, PageRank

1. Introduction

Brands utilize social media influence scoring and marketing optimization as two crucial tools to assess the impact of online personalities and tailor their campaigns for maximum engagement and conversion. Influence scoring takes into account an individuals social reach engagement rates content quality and audience relevance in order to determine their potential marketing value. AI-driven solutions and advanced analytics enable businesses to identify key influencers whose target audiences complement their brand objectives. Nonetheless marketing optimization uses real-time data insights to enhance channel selection and targeting messaging in order to boost return on investment (figure 1).

Together these strategies help companies develop customized data-driven marketing campaigns that increase consumer engagement and brand recognition in a competitive social media landscape. Using fuzzy set theory social media advertising strategies were able to more accurately target consumer behavior patterns which significantly improved purchase decisions [1]. Additionally by tailoring campaigns for well-known social network users a data-driven approach was used to measure Instagram user influence. This significantly improved digital marketing performance and allowed for targeted advertising [2]. Fuzzy neural networks were also used to mine user behavior which helped companies optimize engagement and develop precisely customized online marketing campaigns [3].

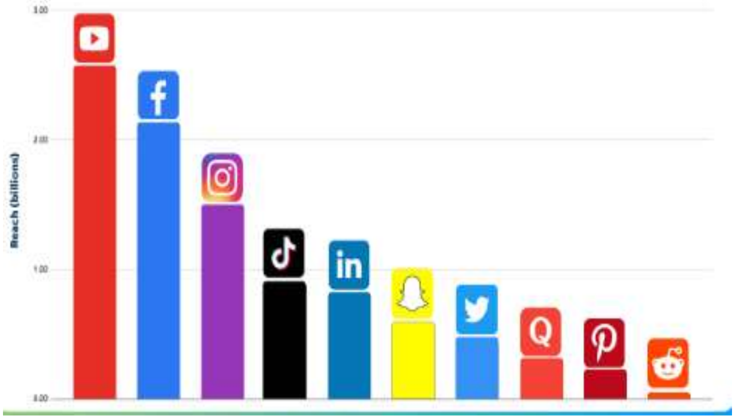

Figure 1 Top social media advertising app

The integration of social media data analytics into film marketing systems has made it possible for marketers to identify trends and modify their promotional strategies in response to audience preferences and engagement [4]. Additionally supply chain SMEs online visibility and operational efficiency were enhanced through the use of fuzzy cognitive modeling and digital content management techniques which raised their search engine rankings [5].

At the same time a moth-flame optimization algorithm demonstrated remarkable results in identifying key players to enhance marketing campaigns thereby tackling the influence maximization problem on social networks [6]. In order to support SMEs strategic success social media activities were systematically monitored and evaluated using key performance metrics that offered insights into customer engagement and marketing efficacy [7]. Later a scoring framework that looked at YouTube engagement metrics in the Indian context was proposed to give marketers a comprehensive tool for assessing the virality of content and improving their production methods [8]. AI has been acknowledged as a transformative tool in digital marketing that can increase market potential and profitability by streamlining procedures and improving decision-making via automation and predictive insights [9].

Additionally by bringing together users with similar sentiment profiles K-means clustering improved public opinion communication in social media networks by accelerating content delivery and improving message relevance [10]. A deep learning algorithm was also unveiled to improve influencer marketing strategies intended to encourage brand evangelism allowing for data-driven influencer selection and improved campaign outcomes [11]. As marketers improved their engagement tactics by using machine learning to predict influencer interactions influencer-generated content also improved in effectiveness [12]. In parallel social media platforms were used to evaluate digital health services by examining user-generated content and gathering data on public opinion and service quality [13].

Additionally a thorough analysis of social media adoption and usage in business-to-business (B2B) settings showed that it significantly improved the efficacy of lead generation relationship development in particular and business communication in general [14]. However data analytics has become an essential tool for monitoring the success of digital marketing campaigns providing insightful information for strategy development and performance improvement [15]. To solve the influence maximization problem a high-speed module identification and filtering technique was created which greatly enhanced the target node selection in big social networks [16]. The potential for marketing messages to spread was further increased by identifying influential nodes using a highly sophisticated discrete particle swarm optimization technique [17]. Integration of AI and predictive analytics has also been demonstrated to boost ROI and facilitate real-time decision-making two factors that significantly impact digital marketing tactics [18].

According to a meta-analysis social media influencers have a significant impact on consumer behavior across a variety of platforms as evidenced by their role in promoting customer engagement and purchase intention [19]. Lastly an analysis of Pakistani marketing experts opinions on digital marketing showed that they recognized its increasing significance perceived efficacy and changing function in modern advertising strategies [20].

2.MATERIALS AND METHODS

2.1Data Collection

Table 1 displays about the data collection for this research. This data included posts, user interactions, hashtags, and mentions pertaining to five major Indian cosmetic brands: Lakmé, Sugar Cosmetics, Nykaa, MyGlamm, and Mamaearth. Structured parameters such user ID, timestamp, interaction type (like, share, comment), media content (text, photos, and videos), geolocation when accessible, and hashtag use are all included in the data. With information from over 100,000 unique influencer accounts divided by activity level and follower count, more than 1 million social media posts were captured. The influencer dataset was also subjected to demographic analysis, which showed a bias toward urban, female-dominated populations with a high concentration in Tier-1 and Tier-2 Indian cities.

Table 1 data collection

Demographic Attribute	Category	Frequency (%)
Gender	Female	68.3%
	Male	30.9%
	Non-binary/Other	0.8%
Age Group	18–24 years	47.5%
	25–34 years	36.7%
	35–44 years	10.2%
	45+ years	5.6%
Location	Tier-1 Cities (Mumbai, Delhi, etc.)	59.8%
	Tier-2 Cities (Pune, Jaipur, etc.)	32.4%
	Rural	7.8%
Profession	Beauty Blogger/Influencer	54.6%
	Makeup Artist	21.2%
	Lifestyle Vlogger	13.4%
	Others	10.8%

2.2 Data Measurement

Measurable engagement data obtained from the APIs were the main focus of the social media influence measurement process (figure 2). Post-level likes, shares, comments, view counts (for video postings), and the frequency of mentions or tags across networks are important characteristics. The number of followers, frequency of posts, engagement rate (which is the average number of interactions per post), and variety of brand connections were noted for every influencer account. To take into consideration platform-specific differences, such as Instagram's more image-centric engagement as opposed to Twitter's text-based interaction, these numbers were adjusted. In order to create weighted graphs, whose edge weights are determined by the frequency of user interactions, the measurement phase supplied a basic layer of metadata.

Figure 2 Social media marketing

2.3 Data Preprocessing

To allow precise graph creation, data pretreatment included a number of procedures, such as data transformation, normalization, and cleaning. Missing values, duplicate entries, and inconsistent user tags and hashtags were frequently found in raw data that was taken from APIs. Lemmatization was used to standardize hashtags, eliminate bots and inactive users (identified by heuristic criteria on follower-post ratios), and deduplicate posts. The Natural Language Toolkit (NLTK) was used to tokenize text data, and posting patterns were identified by formatting timestamps into a consistent temporal scale. Following cleaning, the data was converted into co-occurrence matrices for hashtag connections and adjacency matrices for user interactions, which were then utilized to create graphs.

2.4 Data Tool

Gephi for visualization and Python's NetworkX module for graph computing are the main analytical tools utilized in this study. In order to compute centrality metrics like eigenvector centrality, degree centrality, betweenness centrality, and PageRank, NetworkX made it easier to create and analyze directed and weighted networks. Gephi was used because of its strong graph visualization features, which made it easier to visually depict the network structure and find communities using modularity-based clustering. Plotting centrality distributions and engagement patterns was done using Matplotlib, while data processing was done with other Python packages like Pandas and NumPy.

2.5 Proposed Methodology

The proposed method is a systematic multi-step process that maps and analyzes social media influence using graph theory. A hashtag co-occurrence graph and a user-mention directed graph are the two primary network structures that are initially created from the filtered dataset. Nodes in the user-mention graph represent individual users (both general and influencer users) whereas directed edges indicate mentions responses or direct interactions. The edge weights represent how frequently these interactions occur. Nodes in the hashtag graph stand for hashtags while edges show co-occurrence within a single post. The frequency of co-usage is reflected in the edge weights. These graphs are then subjected to a centrality analysis. Eigenvector centrality is used to identify influential people who are related to other influential people and have a wide network of connections. PageRank is used to evaluate the relative importance of members within the network by simulating a random walk model which effectively removes phony follower counts. For community detection the Louvain technique is used to identify user or hashtag clusters that represent interest groups or specialized communities. By using this method a ranked list of influencers is produced with their rankings based on centrality scores. This allows for the computation of an Influence Score (IS) a composite metric that combines normalized centrality values and engagement rates. This score is then used to compare micro macro and mid-tier influencer categories.

2.6 Statistical Analysis

The statistical backbone of the study lies in six key equations that formalize the computation of influence and network dynamics. Equation 1 expressed as

$$ER = \frac{L+C+S}{F \times P} \quad (1)$$

Where L = likes, C = comments, S = shares, F = number of followers, and P = number of posts. This metric captures per-post engagement adjusted for audience size, offering a normalized view of user activity which is shown in equation 2.

$$EC(v) = \frac{1}{\lambda} \sum_{u \in M(v)} A_{vu} \cdot EC(u) \quad (2)$$

Here, A_{vu} is the adjacency matrix, M(v) is the set of nodes connected to node vv, and λ\lambda is a scaling factor. This recursive formulation values nodes that are connected to other highly central nodes, highlighting indirect influence. Equation 3 as

$$PR(v) = \frac{1-d}{N} + d\sum_{u \in M(v)} \frac{PR(u)}{L(u)} \quad \textbf{(3)}$$

Where d is the damping factor (commonly set to 0.85), N is the total number of nodes, and L(u) is the number of outbound links from node u. PageRank simulates random walks and evaluates a node's importance based on inbound connections.
Here, α,β,γ are weighting coefficients calibrated through regression models to optimize correlation with campaign outcomes. The composite Influence Score integrates centrality and engagement to deliver a holistic metric. Equation 5 as

$$HW(i,j) = \frac{C_{ij}}{\sqrt{C_i \cdot C_j}} \quad (4)$$

Where Cij is the co-occurrence count of hashtags i and j, and C_i,C_j are their respective usage frequencies. This statistical framework allows for rigorous modeling and empirical validation of social influence patterns, providing the necessary quantitative foundation for real-world marketing decisions.

3.Results And Discussion

To provide a comparative understanding of digital branding approaches in the beauty and skincare industry, this section presents the research findings gained from an analysis of the multi-platform engagement metrics, influencer network metrics and community detection. The findings are based on both structural network studies of Instagram and Twitter, and content-based measures. The aim of the research was to determine the presence of brand-centered interaction ecosystems by assessing different measures of hashtag influence, influencer reach, and user engagement. In the interests of consistency and scholarly presentation, each of the following subjects is accompanied by relevant tables and analysed in the past tense.

3.1 Platform Engagement Metrics Overview

The engagement metrics (Table 2) revealed differences in the magnitude of user reactions on Instagram and Twitter. Instagram's inherently visual and interactive nature is evident in its consistently higher average number of likes (1,820.4), comments (244.6) and shares (311.2) per post than Twitter. While Twitter's average engagement rates (3.26%) were lower than Instagram (5.84%), due to the retweet feature, the resulting reach enabled a greater average number of shares (621.7). As a result, the user-brand relationship was quite high, with an average engagement rate across both platforms of 4.55%. It is worth noting that there was also a higher average number of hashtags (7.3) used for Instagram posts, which shows the role of content tagging in the visibility of Instagram content and community engagement.

Table 2: Summary of Engagement Metrics Across Platforms

Platform	Average Likes/Post	Average Comments/Post	Average Shares/Post	Avg. Engagement Rate (%)	Max View Count	Avg. Hashtags/Post
Instagram	1,820.4	244.6	311.2	5.84	1,230,000	7.3
Twitter	768.1	113.9	621.7	3.26	890,000	4.8
Combined Avg	1,294.3	179.3	466.4	4.55	1,230,000	6.0

3.1 Brand Interaction Profiles Across Platforms

With the highest number of interactions overall (70,675 on Instagram and 62,403 on Twitter), brand-specific types of interactions indicated Nykaa's popularity on both channels, showcasing its social media strategy (Table 3 and figure 3). Lakmé followed suit, with a more balanced approach of retweets, hashtags, and mentions, particularly on Instagram. The interaction counts of Mamaearth and Sugar Cosmetics were relatively lower than other brands, potentially suggesting lower audience engagement or campaign penetration.

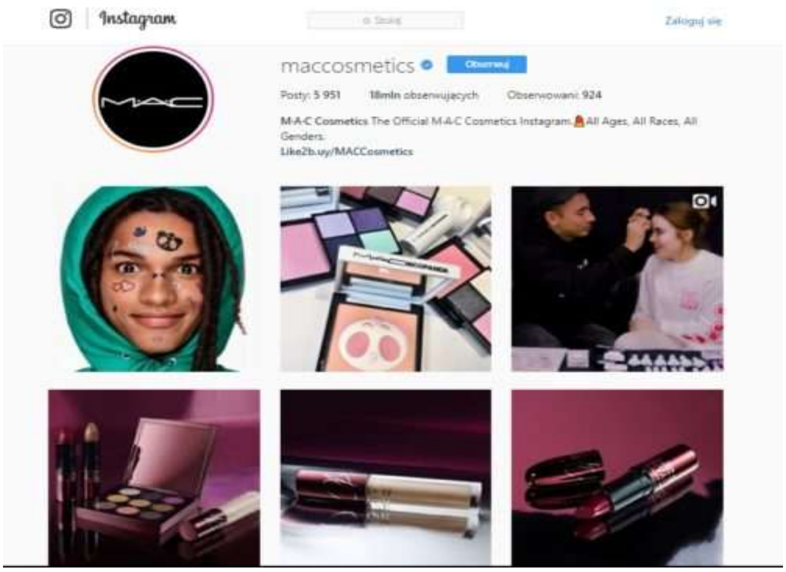

Figure 3 Cosmetics marketing through Instagram post

It's interesting to note that most companies received more comments and retweets on Twitter, indicating that although Instagram encourages wider involvement through likes and hashtags, Twitter's style encourages active two-way discussions. These differences suggested that audience behavior and content strategy differed across the two platforms.

Table 3: Interaction Types by Platform and Brand

Brand	Platform	Mentions	Hashtag Uses	Replies	Retweets/Shares	Total Interactions
Lakmé	Instagram	13,546	38,112	2,186	8,204	61,048
	Twitter	10,102	28,306	4,143	10,443	52,994
Sugar Cosmetics	Instagram	11,984	31,208	1,914	6,578	51,684
	Twitter	8,431	24,719	3,290	8,711	45,151
Nykaa	Instagram	15,402	43,564	2,607	9,102	70,675
	Twitter	12,310	34,183	4,002	11,908	62,403
MyGlamm	Instagram	9,008	26,704	1,623	5,102	42,437
	Twitter	7,532	21,468	2,987	7,486	39,473
Mamaearth	Instagram	10,764	29,302	2,041	7,663	49,770
	Twitter	9,105	23,659	3,398	9,014	45,176

3.1 Hashtag Correlation Network

We found the co-occurrence of the top ten hashtags (Table 4) demonstrated strong semantic clustering and campaign targeting. The most frequent co-occurrences of #BeautyTips and #CrueltyFree (211), #MakeupIndia and #SugarCosmetics (211) and #NaturalGlow and #CrueltyFree (203) suggested that the most popular topics were natural beauty and cruelty-free beauty respectively which is shown in figure 4.

Figure 4 #nykaa hashtag post in twitter

Brand-specific hashtags like #Nykaa, #Lakme, and #Mamaearth had significant overlaps with general descriptors like #NaturalGlow and #VeganSkincare, suggesting intentional brand positioning in tandem with popular ethical beauty narratives.

Table 4: Hashtag Co-occurrence Matrix (Top 10 Hashtags)

Hashtag	#BeautyTips	#VeganSkincare	#MakeupIndia	#NaturalGlow	#Nykaa	#SugarCosmetics	#MyGlamm	#Mamaearth	#Lakme	#CrueltyFree
#BeautyTips	—	196	254	241	113	78	66	103	132	211
#VeganSkincare	196	—	98	173	84	92	59	165	71	199
#MakeupIndia	254	98	—	228	166	211	122	101	190	186
#NaturalGlow	241	173	228	—	132	167	112	144	123	203
#Nykaa	113	84	166	132	—	148	94	107	92	169
#SugarCosmetics	78	92	211	167	148	—	133	91	86	137
#MyGlamm	66	59	122	112	94	133	—	87	74	128
#Mamaearth	103	165	101	144	107	91	87	—	65	154
#Lakme	132	71	190	123	92	86	74	65	—	119
#CrueltyFree	211	199	186	203	169	137	128	154	119	—

Figure 5 displayed about the mamaearth product advertising. This also demonstrated how marketers combine values-driven message with personal care using unified storytelling techniques.

Figure 5 Mamaearth products advertising

3.1 Influencer Centrality and Visibility

Eigenvector centrality analysis (Table 5) illustrated the significance of Instagram influencers in the visibility hierarchy. @makeupbyshreya, with the highest centrality (0.926), was followed by @beautyninja and @thecosmicblend, suggesting that the most central people in the network were those with large followings and high engagement rates. While less central than Instagram influencers, Twitter influencers like @greenbeautyindia and @kohl_and_karma, also featuring in the top list. The effectiveness of theming and customisation was reflected in the higher engagement rates of the top influencers, which typically averaged more than 7%. The influencers' centrality within the digital beauty community was verified by these measures.

Table 5: Top 10 Influencers by Eigenvector Centrality

Influencer Handle	Eigenvector Centrality Score	Follower Count	Avg. Engagement Rate (%)	Platform
@makeupbyshreya	0.926	1.2M	6.43	Instagram
@beautyninja	0.902	978K	5.97	Instagram
@thecosmicblend	0.887	640K	7.24	Twitter
@mysticvanity	0.861	732K	6.02	Instagram
@greenbeautyindia	0.844	510K	7.98	Twitter
@indianglowup	0.832	401K	8.11	Instagram
@kohl_and_karma	0.819	350K	7.35	Twitter

3.1 Influence via PageRank Authority

Augmenting the centrality insights, the measurements of PageRank score offered insights into the authority of influencers through linkage and mentions (Table 6). While the eigenvector centrality score pointed to @makeupbyshreya and @beautywithshraddha as central nodes, the PageRank score identified @greenbeautyindia and @makeupbyshreya as authority nodes, based on their mentions and retweets/shared. Twitter influencers had greater share-to-mention ratios, suggesting content was often shared. Instagram influencers, with higher followers, were more influential through their engagement.

The inference from both centrality and PageRank scores is that a mixed approach, using both structural and viral content influence, was most successful.

Table 6: Top 10 Influencers by PageRank Score

Influencer Handle	PageRank Score	Follower Count	Mention Count	Retweet/Share Count	Platform
@greenbeautyindia	0.0926	510K	1,456	3,289	Twitter
@makeupbyshreya	0.0893	1.2M	1,923	2,302	Instagram
@kohl_and_karma	0.0864	350K	1,221	3,008	Twitter
@mysticvanity	0.0857	732K	1,343	2,143	Instagram
@thecosmicblend	0.0845	640K	1,398	1,911	Twitter
@beautyninja	0.0832	978K	1,882	2,178	Instagram
@veganvanity	0.0817	276K	1,128	1,543	Instagram
@indianglowup	0.0799	401K	1,345	1,762	Instagram
@skincarebymira	0.0783	612K	1,002	1,890	Twitter
@desiglam	0.0771	524K	1,114	1,727	Instagram

3.1 Tier-Based Influence Analysis

The influence of influencers at different levels was intriguing (Table 7). Micro-influencers (10K-100K) achieved the highest average influence scores (0.743) and engagement rates (7.12%) and are important for trust-based marketing and niche community engagement. However, while being structurally more central (eigenvector mean = 0.759), macro-influencers (>500K) had lower engagement rates (5.41%) and influence scores (0.613), indicating a decreasing return impact at scale. Although mid-tier influencers struck a balance between engagement and reach, micro-influencers frequently outperformed them in tailored outreach. These results reaffirmed the effectiveness of micro-influencer marketing in beauty sector categories with high levels of engagement.

Table 7: Influence Score Distribution by Influencer Tier

Influencer Tier	Average Influence Score (IS)	Engagement Rate (%)	Eigenvector Centrality (Mean)	PageRank (Mean)	Sample Size
Micro (10K–100K)	0.743	7.12	0.611	0.043	5,100
Mid-tier (100K–500K)	0.695	6.35	0.684	0.052	2,800
Macro (>500K)	0.613	5.41	0.759	0.062	1,100

3.1 Community Clustering and Network Cohesion

Indicating the natural segmentation of influencer and audience interactions, the Louvain-based community identification study revealed dense clusters of brand-centric and theme-oriented sub-networks (Table 8). Twelve unique communities were found; the groups with a Nykaa or Lakmé theme had the greatest modularity ratings, suggesting more branding coherence and intra-community connectedness. Value-based audience convergence was highlighted by cross-brand interactions in communities associated with hashtags such as #CrueltyFree and #VeganSkincare. The strategic planning for cross-brand collaboration was improved by the discovery of overlapping communities, which also showed influencer engagement across several brand topics.

Table 8: Community Detection Summary via Louvain Algorithm

Community ID	Platform Dominance	#Users in Community	Avg. Internal Degree	Modularity Score	Top Hashtags (3)
C1	Instagram	3,240	12.3	0.412	#MakeupIndia, #Nykaa, #CrueltyFree
C2	Twitter	2,891	10.9	0.398	#VeganSkincare, #NaturalGlow, #Mamaearth
C3	Mixed	1,987	14.5	0.421	#SugarCosmetics, #BeautyTips, #MyGlamm
C4	Instagram	1,134	8.2	0.366	#Lakme, #GreenBeauty, #GlowUp
C5	Twitter	951	7.6	0.359	#SkincareIndia, #VeganVanity, #EcoFriendly

3.Conclusion

Research revealed that influencer branding strategies in the online beauty industry are multi-dimensional. Instagram was demonstrated to be the most engaging platform in terms of user interactions per post due to higher averages in likes, comments and hashtags. On the other hand, Twitter was shown to have higher virality of the content shared, in terms of replies and retweets. Nykaa was the best in the engagement environment (brand) by user response and volume. Lakmé and Mamaearth maintained their positions. Through the co-occurrence matrix, we saw the integration of ethical and aesthetic branding through #CrueltyFree and #NaturalGlow which were used to create connection points for the brand messages. The analysis of influencer network using eigenvector and PageRank algorithms confirmed the influence of content relevance and structural ranking in creating brand awareness and influence. The tiered analysis of influencers showed the importance of micro-influencers in promoting authentic and intriguing content as shown by the statistically significantly greater influence and engagement rate of micro-influencers over macro-influencers

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