Examining Platform Strategy for Influencer Marketing Using Text Mining

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***Abstract*—Social media influencer marketing is widely accepted as an effective approach for companies and brands to reach target consumers and allows advertisers to gather consumers' feedback in real time. There is limited research on the investigation of the efficacy of influencer marketing based on platform strategy, as most literature attributes the success of influencer marketing to that of the source (influencers) and message (content). To fill this gap in research, this study utilizes natural language processing to examine social media users' responses to influencers' advertisements by mining their textual comments on three different major social media platforms: Facebook, YouTube, and X (formerly Twitter). By comparatively analyzing the nature of social media user responses on three different platforms, specifically the evaluation of the advertising messages, varying insights can be gleaned on the efficacy of social media platforms for influencer marketing. The results of sentiment analysis and topic modeling indicate that Facebook yields the most positive responses to advertisements in influencer-generated content as social media users display strong fandom behavior. Moreover, social media users tend to indicate purchase intentions and leave post-purchase reviews on X while forming discussions around the contents of the advertisement on YouTube.**

Keywords—influencer marketing, text mining, sentiment analysis, natural language processing, social media

I. INTRODUCTION

Social media influencer marketing was valued at $16.4 billion in 2022 and is estimated to reach a record-breaking $21.1 billion in 2023 according to Statista [1]. Before the rise in the popularity of social media influencers, the use of celebrity endorsers was known to be one of the most attractive strategies for marketers as celebrities encompass the ability to "draw audiences, transfer their image or values onto products or brands, and influence consumers' purchase intentions" [2]. Influencers have been discovered to have similar effects, or perhaps even better. Unlike traditional celebrities, social media influencers (SMIs) are unique individuals who establish their fame through a series of successful and viral self-generated content on social media. Therefore, they are viewed commonly as key opinion leaders who have "established likable personalities by regularly creating and disseminating content – usually online or on social media – and have accumulated a large number of followers" [3, 4]. It is common today for influencers to obtain millions of subscribers or followers. Although SMI's popularity and "unique advantages," as 94% of marketers assess their influencer marketing strategy to be effective [5, 6] have been widely recognized, limited studies have directely investigated the efficacy of individual social media platforms for various influencer marketing efforts. Therefore, this study aims to fill this research gap by examining influencer marketing efficacy across three different major social media platforms, Facebook, YouTube, and X (formerly Twitter), to comparatively analyze social media users' responses to influencer-generated advertisements.

II. LITERATURE REVIEW

A. Reaching Target Audience

From identifying specific demographics through zip codes and the applications of artificial intelligence technologies to optimize the reach of target audiences [7], target advertising strategies are essential to achieving advertising objectives. Therefore, successfully delivering an intended paid message to the desired target audience is the goal of any advertising strategy, and social media platforms are crucial to consider in targeting specific consumers. However, much of the practical and scholarly focus has been skewed toward advertisement execution, such as content strategy and choosing the right influencer to work with [8, 9]. Most literature attributes successful influencer marketing to that of the source (influencers) and message (content), but Voorveld et al. [10] argue that consumers' engagement with social media platforms affects their advertising evaluations. There is limited research on the investigation of the efficacy of influencer marketing based on which social media platform is chosen to deliver advertisements, especially by means of analyzing actual user-generated data mined from social media platforms.

Therefore, this study examines social media users' responses to influencer advertisements by mining their textual comments on three different major social media platforms. By comparatively analyzing the nature of social media users' responses to influencers' advertising messages, specifically through topic modeling and sentiment analysis, insights can be gleaned on the efficacy of social media platforms to inform the most effective social media influencer marketing strategies.

B. Influencer Marketing

Social media has been taken over by influencer marketing as it is widely accepted as a cost-effective approach for companies and brands to reach existing and potential consumers directly in real time [11]. Many studies attribute the success of social media influencer marketing to the parasocial relationship formed between influencers and their followers [12]. Others find that the

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success of influencer marketing lies in the influencers' unique attributes and characterizations, such as trustworthiness and perceived expertise [13]. Particularly, trust was found to play a large role in mediating the impacts of authenticity on loyalty and marketing effects [14]. Similar theoretical frameworks can be found in traditional celebrity endorsements on the impacts of consumers' purchase intentions and consumer engagement [2] and their effectiveness in the digital environment [15]. However, there is a gap in research examining varied outcomes of social media influencer marketing due to platform differences. As social media continues to evolve, new platforms have continued to emerge. Every platform is distinct, such that Facebook, YouTube, TikTok and X are distinct in content format (video, texts, images-based content) and engagement type. Therefore, the demographics and behavior of the audience and their engagement differ significantly across platforms. To fill this gap in research, this study examines consumer responses and sentiments toward influencer advertisements on three different major platforms.

C. Natural Language Processing

Natural language processing (NLP) is a domain within computational linguistics that focuses on deriving insights from unstructured textual data. NLP deals with the interaction between computers and human language, enabling machines to understand, interpret, and generate text. Building on the foundational techniques of NLP, text mining involves the extraction of meaningful patterns, information, or knowledge from large volumes of text, turning qualitative data into quantifiable insights. Topic clustering or topic modeling, a technique of text mining, specifically aims to discover abstract topics or themes within a collection of documents. NLP, text mining, and topic clustering collectively underscore the importance of harnessing the vast amount of information hidden in text and making it accessible for various applications, from information retrieval to sentiment analysis.

NLP is widely used in research across multiple disciplines. A few examples that harness these techniques include sentiment analysis of social media data [16, 17], medical research [18], customer feedback analysis [19], etc.

D. Social Media Platforms

There are large differences in the audience makeup of social media platforms. According to Sprout Social, Facebook, a social networking site launched in 2004, has 2.91 billion active monthly users with the largest (31.5%) group of users aged between 25 and 34 [20]. Facebook is the largest social platform among consumers and serves as the mecca for advertisers [20]. However, the shift of younger users to different platforms has been noted in the past few years. YouTube is the second most popular social media network worldwide. It has 2.2 billion active monthly users to date, reaching largely those between 15 and 35 years of age [20]. YouTube users are much younger as the preference for video content grows, but they tend to turn to YouTube for entertainment rather than for information on brands and products [20]. Lastly, X is a popular social networking site that allows users to send and receive short messages called "tweets." A popular platform known for discussion of breaking news and events, X has 450 million active monthly users [21], and users between the ages of 18 to 29 make up the largest group (42%) on X [20]. Most interestingly, more than a third of X's audience are college-educated and make more than $75,000 annually [20]. According to the Pew Research Center, Facebook and YouTube continue to dominate the social media landscape, with 81% and 69% of U.S. adults utilizing these platforms respectively [22].

In addition to their popularity, differences in modality and perceived value of each platform may factor into how information is received by users. X is primarily a text-based platform and YouTube is a video-based platform, while Facebook combines both visuals and text. Therefore, the presentation of advertisements from influencers, although showcasing the same product or brand, may vary depending on the platforms they're on. In order to comparatively analyze consumer responses to social media influencer marketing on different platforms, the following research questions are proposed:

- **RQ1:** What is the nature of social media users' responses to influencer-generated advertisements on each of the following social media/platforms: Facebook, YouTube, and X?
- **RQ2:** What is the nature of social media users' advertising evaluation on each of the following social media/platforms: Facebook, YouTube, and X?
- **RQ3:** What is the general sentiment expressed by social media users on influencer-generated advertisements on each of the following social media/platforms: Facebook, YouTube, and X?

III. METHOD

A. Data Collection

For this preliminary study, two "mega" influencers were identified in the same gaming content genre/category who are comparable in popularity (i.e., Influencer I has 35.7 million YouTube subscribers; Influencer II has 34.1 million YouTube subscribers). For each of the influencers, a product/brand that was promoted across all three platforms was identified. Data from three social media platforms, Facebook, X, and YouTube were collected through registered API (Application Programming Interface). For Influencer I, the promotion of a clothing brand was chosen, and 331 comments from Facebook, 212 tweets from X, and 2,575 comments from YouTube were collected. For Influencer II, the promotion of a mobile video game was chosen and 668 comments from Facebook, 81 tweets from X, and 380 comments from YouTube were collected. It should be noted that engagement levels and number of comments to influencer-generated advertisements were observed to be significantly lower than non-advertisement influencer content.

B. Text Mining

All comments that were mined were processed and analyzed using SAS Enterprise Miner and Text Miner 15.2 to extract the underlying key topics or themes in textual documents. The tool allows the grouping of similar documents—called clusters—based on terms and their frequency of occurrence in the corpus of documents and within each document [23]. The data were processed through text parsing, text filtering, and text topics in

SAS Text Miner. Different parts of speech, noun groups, and multi-word terms were identified and the tokenization process separated each document into individual words and eliminated unnecessary words by applying stemming, lemmatization, and synonyms. The number of terms or documents was reduced to be included in the text analysis. After parsing the corpus, the term weights and frequency weights were configured to reduce the number of extracted words. Finally, topic modeling, a probabilistic clustering algorithm, was used to discover topics or themes that are present in an unstructured text.

C. Sentiment Analysis

Orange Data Mining tool [24] was used to measure the sentiments of the users' comments. Liu-Hu [19] and VADER [25] sentiment analyses were executed to yield sentiment scores for each document in a corpus. The Liu-Hu sentiment analysis is based on the idea of maintaining lists of words that convey either positive or negative sentiments. Each word in the list has a polarity indicating whether it is positive, negative, or neutral. VADER sentiment score was built for social media text. It uses a combination of a sentiment lexicon, a set of grammatical and syntactical rules, and a set of heuristics to be specifically attuned to the sentiments expressed in social media. VADER handles negations, amplifiers, and diminishers and it not only gives a positivity and negativity score but also tells us how positive or negative the sentiment is. The algorithms are based on NLTK (Natural Language Toolkit) [26] which is a leading platform for building Python programs to work with textual data. To find the general sentiment of the users' comments on a platform, the sentiment scores of each user's comments were averaged.

IV. Results

A. Influencer I – Facebook

We generated 11 topics (See Table I) which were then grouped into two themes. The first theme observed was fandom. Social media users who reacted to the influencer-generated advertisement displayed fandom behavior. Influencer I cleverly integrated the advertisement into an inside joke/meme to which the groups of fans responded positively and enthusiastically. Influencer I's fans recognized the post as an advertisement yet reacted as they would have to the influencer's non-advertisement content. They displayed the behaviors of a supportive fan and did not express any negative feelings. Social media users also attempted to communicate with the influencer by leaving comments about how much they love the influencer's video games and stating that they are long-term, loyal followers. The second theme was about the influencer himself and his attempts to engage with the influencer. Social media users left comments to wish the influencer a happy birthday and shared that they watch the influencer's content often. The comments on the Facebook post did not yield much direct conversation about the advertised brand. Rather, the discussion was heavily dominated by fans expressing their excitement and support for the influencer's endorsement deal. The sentiment, using the VADER Average Compound score, is 0.351036 (Liu-Hu measure: 5.566999). This indicates that the overall sentiment for Influencer I's advertisement on Facebook is positive.

TABLE I. INFLUENCER I ON FACEBOOK

	Topic	No. of Docs	Description
1	+butter,+sell,bread,time,good	60	Fandom–loyal followers
	know,+look,+fan,+video,+watch	37	
	exotic,+exoticbutter,+butter,+want,+fan	36	
	[influencer],+find,channel,+look,play	29	
	+video,+play,+game,bro,play	24	
	exotic,butters,great, [influencer],+look	20	
2	[influencer],great,+watch,+fan,+year	45	Discussion about influencer
	[influencer],+melt,+look,face,know	36	
	bro,+day,+love,+want, [influencer]	21	
	+birthday,+happy,happybirthday,[influencer],+want	16	
	[influencer],business,mind,+start,+fan	10	

B. Influencer I – X

One topic was identified from two hundred and twelve user comments (See Table II). All comments were about the clothing brand that the influencer promoted in the post. Users acknowledged that the price is expensive but they wanted to purchase the product anyway. Fans became excited for the influencer to refer to his popular but now deleted YouTube channel in this post. It appears as though the influencer strategically used the channel referral as bait to get people to look further into the clothing brand. Additionally, social media users expressed direct purchase intention. The sentiment, using the VADER Average Compound score, is 0.055776 (Liu-Hu measure: -0.42774). This indicates that the overall sentiment for Influencer I's advertisement on X is neutral with a slight positive skew according to VADER. Liu-Hu is slightly negative.

TABLE II. INFLUENCER I ON X

	Topic	No. of Docs	Description
1	-annus,unus,death,life,+tick	25	Purchase intention
	-money,lol,[influencer], cloak, death	16	
	-[influencer],cloak,+know,korean,annus	12	

C. Influencer I – YouTube

Eight topics were generated which were then organized into two themes (See Table III). Most of the comments were about the details that occurred in the YouTube video. Social media users commented on the influencer's physical appearance and expressed how surprised they were that the endorsed clothing brand included pants. Other comments indicated that they have a positive interest in the brand despite the expensive price tag. The comments mentioned the influencer's endearing behavior in the video along with the brand that was endorsed. The sentiment, using the VADER Average Compound score, is 0.2351 (Liu-Hu measure: 5.282051). This indicates that the overall sentiment for Influencer I's advertisement on YouTube is slightly positive.

TABLE III. INFLUENCER I ON YOUTUBE

	Topic	No. of Docs	Description
1	+pant,eat, [influencer],+want,+pair	393	Discussion of details occurring in the video
	+[influencer], +wear, +fall, couch, +leg	309	
	+video, [influencer], +good, +watch, +love	253	
	+[influencer], +wear, +leg, +pant, +short	217	
	+fall,man,+sexy,+ [influencer],couch	187	
	+pant,wear,+wear,[influencer],don't	186	
	lol,xd,+love,+fall,+good	104	

	Topic	No. of Docs	Description
2	+cloak,+want,+buy,+price,+brand	285	Product discussion

D. *Influencer II – Facebook*

Fourteen topics were generated and organized into two topics (See Table IV). The first topic largely reflects comments about the influencer's physical appearance with words such as "wow," "sweet," "amaze," and "look." These comments had no relevance to the contents of the video or the brand that was promoted. They were solely compliments, encouragements, and acknowledgments of the influencer's physical appearance and her content. The second topic was fandom. Again, people commented more on how much they loved the influencer instead of the game that the influencer was promoting in the Facebook post. The sentiment, using the VADER Average Compound score, is 0.536842 (Liu-Hu measure: 35.67292). This indicates that the overall sentiment for Influencer II's advertisement on Facebook is positive – this is the highest positive sentiment among all platforms across both influencers.

TABLE IV. INFLUENCER II ON FACEBOOK

	Topic	No. of Docs	Description
1	old,+watch,[influencer],+year, [influencer]	61	Discussion about influencer
	+love,+video, [influencer],[influencer],+friend	59	
	+video,+watch,day,+know, [influencer]	54	
	nice,pic,+friend,meet,sniper	51	
	beautiful,+post,+look,+house,amazing	40	
	[influencer],+friend,vids,facebook,account	33	
	+look,+amaze,youtuber, [influencer],+look	27	
	love,+amaze,always,channel, [influencer]	25	
	cute,channel,sweet,vids,youtube channel	17	
	good,pic,sweet,nice, [influencer]	16	
	wow,+know,+video,+friend,sweet	11	
2	+fan,+big,big fan,huge,+biggest fan	30	Fandom
	+want, [influencer],+talk,+know,support	30	
	+good,morning,good morning, [influencer],old	12	

E. *Influencer II – X*

As the data set for X is rather small with only 81 tweets, only one topic was generated (See Table V). The influencer links a YouTube video to this tweet. Users commented on the game character portrayed by the influencer and the mobile game that is advertised on X. Social media users indicated purchase intention as they commented that they had downloaded the game and also left post-purchase reviews by commenting that they "love the game". People shared their own game characters and expressed that they love playing the game. The sentiment, using the VADER Average Compound score, is 0.53502 (Liu-Hu measure: 16.51673). This indicates that the overall sentiment for Influencer II's advertisement on X is positive, similar to the Facebook platform.

TABLE V. INFLUENCER II ON X

	Topic	No. of Docs	Description
1	+game,+love,+character,+look,+play	16	Purchase intention

F. *Influencer II – YouTube*

Seven topics were generated which exemplifies one large theme (See Table VI). Most of the comments were about the content of the video that the influencer posted. Much of the conversation focuses on how the influencer's actions in the YouTube video. Social media users focused on the character of the game that Influencer II promoted in the video. People related to the game character that the influencer was pretending to be "in real life." The sentiment, using the VADER Average Compound score, is 0.354339 (Liu-Hu measure: 8.96115). This indicates that the overall sentiment for Influencer II's advertisement on YouTube is slightly positive.

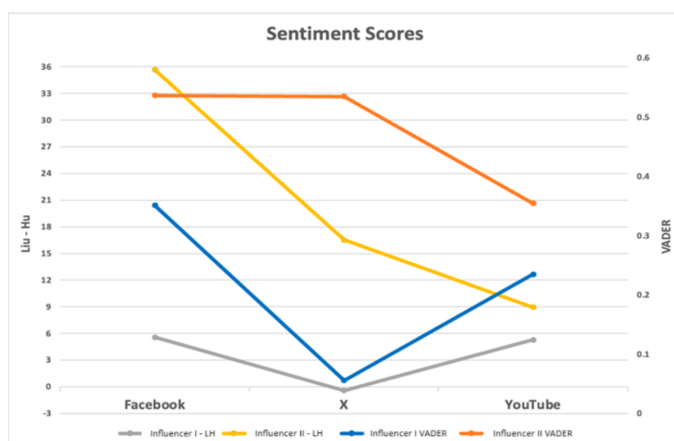
TABLE VI. INFLUENCER II ON YOUTUBE

	Topic	No. of Docs	Description
1	love,+video,+[influencer],bts,+rock	27	Discussion of details occurring in the video
	[influencer],plz,love,+look, [influencer]	22	
	love, [influencer], [influencer],+video,know	20	
	[influencer], [influencer], +novel, martial,+art	17	
	lol,+rock,cute,+crystal,love	16	
	+look,know,cute, [influencer],+fact	11	
	lol,cute,love,+start,anime	10	

V. SUMMARY OF SENTIMENT ANALYSES

The Orange mining tool produces a compound score that corresponds to the sum of the valence score of each word/term in the lexicon and determines the degree of the sentiment. Its value is between -1 (most extreme negative sentiment) and +1 (most extreme positive sentiment) with zero being the neutral score. To find the general sentiment of the users' comments on a platform, the sentiment scores of each user's comments were averaged. comments that the Orange mining tool did not produce a sentiment measure for, such as a neutral score, were not counted.

Fig. 1. Sentiment Scores for Liu-Hu and VADER



All of the VADER sentiment scores were positive for Facebook and it was also the most positive among the three platforms for both influencers. Similar results for Liu-Hu measures were observed. One interesting observation from Fig. 1 is that social media users' responses to Influencer's promotion on Facebook had the most positive VADER sentiment, followed by YouTube, and X. The same pattern occurred for the Liu-Hu sentiment scores for Influencer I where responses to Facebook promotion was the most positive, followed by YouTube, with X resulting in a negative sentiment score. Looking at the VADER and Liu-Hu sentiment scores for Influencer II, the same pattern was observed for all of the platforms, where Facebook was the most positive, followed by X, and then YouTube was the least positive. Although VADER and Liu-Hu use different formulas to indicate sentiment, they both exhibited similar patterns.

VI. Discussion

The nature of social media users' comments in response to Influencer I and Influencer II''s advertisements on each of the three social media platforms, Facebook, YouTube, and X, can be categorized into 3 categories. First, the most prominent theme was "content discussion" which regarded discussion around the details of the social media post's contents. For example, on Influencer I's YouTube video post, fans commented about his pants, while on Influencer II's YouTube video, fans commented about how much they liked the character she was pretending to be to promote a game. Secondly, fandom was displayed as many comments were about the influencer's physical appearance and/or expressing that they are big fans. They left comments as if they were personally communicating with the influencer (i.e., "I love you," "you're so beautiful"). Thirdly, product discussion and purchase intention were identified as a prominent theme. For example, social media users expressed emotions, such as interest and excitement, purchase intention ("I will download the game!"), as well as sharing their post-purchase experience ("I loved your game") on the products/brands that the influencer was advertising through their user-generated content.

Social media platform differences were identified. Facebook was the platform of choice for social media users to display fandom. It was observed to be an intimate platform where fans gather to share inside jokes and have more personal interactions with the influencers (i.e., Happy Birthday wishes). X was identified for both influencers to be the most effective place to advertise as this is where social media users left most comments discussing products. They indicated purchase intent and post-purchase experiences. Finally, YouTube was observed as a place for social media users to form discussions around the contents of the video. Table VII summarizes the prominent themes and platforms from the description of the topics.

TABLE VII. Discussion Summary

Description	Prominent Theme	Prominent Platform
• Discussion of details occurring in the video	Content discussion	YouTube
• Fandom – loyal followers • Discussion about influencer • Fandom	Fandom	Facebook
• Purchase intention • Product discussion	Purchase intention and product discussion	X

Most importantly, although the social media posts were all advertisements, eleven out of twelve sentiment scores were at least slightly positive. This is a unique finding in the age of heightened advertisement avoidance, adblock, and paid subscriptions to avoid seeing advertisements. Despite a generally negative feeling about paid advertisements, the findings suggest that for influencer-generated advertisements, social media users will not only actively seek out their advertisements, but they will engage with and support influencers in their advertising efforts.

VII. Limitations

There are several limitations to this study. First, a limitation inherent to text mining using particular social media platforms is that the user comments are not representative of the general population. Also, there were difficulties in finding influencer content promoting the same product/brand across all three platforms. That was one of the reasons why other popular platforms such as Instagram and TikTok were not included in the study. Therefore, this is a small pilot study using NLP, topic modeling, and text mining to examine the general sentiments of only two influencers across three different platforms. Data gathered for this study from the different platforms were small. A small sample size is less likely to capture the variability and diversity of the larger population, making it less representative. This leads to increased sampling error and the outliers have greater influence. However, even with the small sample size, this study generated useful patterns to produce a concrete conclusion.

VIII. Implications and Future Research

The findings of this study provide both practical and theoretical implications for social media practitioners and scholars alike. Social media marketing's importance in today's digital environment is unequivocal; thus, a robust social media platform strategy provides valuable insights to practitioners who want to maximize their social media influencer marketing efficacy. This preliminary study also provides an additional perspective to influencer marketing research by examining consumer responses in light of platform-based differences rather than the influencer's characteristics and content.

This study examined two popular influencers in the gaming category. Future research should examine a larger sample of influencers across various genres, such as beauty, fitness, travel, etc., to ensure that the differences in the audiences' responses to advertisements will be observed as a result of platform differences and not content genres or specific types of fandoms. Despite the challenges of identifying influencer-generated advertisements for the same product/brand across multiple platforms, larger samples of mined comments will strengthen the results of future studies.

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