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RESEARCH ARTICLE

Exploiting User-Generated Content in Product Launch Videos to Compute a Launch Score

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ABSTRACT This study investigated the relationship between the essential aspects of user-generated content (UGC) and product launch videos to derive the product launch score (PLS). This score can be considered a key performance indicator (KPI) to evaluate the performance of product launch videos. The product launch score can provide businesses and marketers with insights into how well the community and audience perceive a product launch on virtual social media platforms such as YouTube. The authors examined 52 product launch videos with a total of 1,11,716 comments on YouTube and analyzed the data to derive various sentimental, emotional, and social networking aspects from the comments on the product launch videos. Furthermore, the relationship between brand and product mentions was evaluated to determine the centrality of the launch activity. The work determined how effectively the community was engaged with the brand and product launch. Finally, relationship analysis and principal component analysis (PCA) were performed to select relevant aspects for calculating the PLS. This KPI provides a holistic view of user engagement in product launch videos.

INDEX TERMS Text mining, social networks, emotions analysis, word-of-mouth, analytic models, marketing analytics.

I. INTRODUCTION

The primary goal of marketing is to raise awareness regarding products and services in the market and generate leads. Organizations use various communication modes, also known as marketing channels, to reach prospective customers. Traditional marketing channels have witnessed the use of television, radio, and print media to influence, inform, and raise awareness regarding products. However, several problems, including COVID-19, have pushed the world to be more digital process-driven and virtual and rely on new-age digital transformation technologies. Digital channels now allow for tracking customer interactions and feedback, providing valuable data for crafting effective marketing strategies. Consequently, customer interaction using digital channels can help record customer's interaction and feedback, thus serving as a performance measure for designing effective marketing strategies [12].

As a result, social media has emerged as a key communication channel for businesses, enabling interaction, collaboration, and content sharing among users. Social media encompasses a range of activities from sharing information to engaging in discussions that enhance awareness and understanding, even influencing post-purchase behavior without an actual purchase [3], [35]. It has become an integral part of branding and marketing strategies, allowing companies to market their products and services through social networks and websites effectively [49].

Previous research has highlighted the positive impact of social media marketing on customer satisfaction and behavioral intentions [53]. Social media enables businesses to establish brand profiles, offer customer service, and share product information and special offers efficiently and cost-effectively [60]. The strategy involves creating engaging content that promotes products and includes company

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culture, product launches, and more [9]. Such content on social media draws attention to a brand and its offerings, encouraging consumer engagement [61].

YouTube stands out as a preferred digital channel for companies, outperforming other digital marketing channels in creating brand awareness [10], [44]. It allows consumers to seek product information, reviews, evaluations, and unboxings, making virtual product experiences preferable to in-person events. Sentiment analysis of YouTube videos has been used to monitor product launches, indicating the influence of product-related content on consumer behavior [50]. Yet, research has been somewhat limited in scope, focusing on specific channels like beauty and makeup. Several other studies have shown that the content quality of YouTube ads, such as informativeness, entertainment, and trendiness, can positively influence consumer perceptions [50], though reactions to brand assessments can be mixed [28], [67]. These studies shows that marketers often rely solely on interaction scores, overlooking the depth of consumer engagement in comments and discussions.

User-generated content (UGC), like comments and replies, offers more insights into audience perception and engagement with video content. Influencing a purchase decision goes beyond sentiment; the unique impact of review aspects on previous videos is crucial for launching new products effectively. This highlights the opportunity to use UGC to develop a new key performance indicator (KPI) for assessing product acceptance and calculating a product launch score (PLS). This comprehensive score would incorporate sentiments, emotions, and the brand's and product's visibility, diversity, and connectivity, offering a holistic view of consumer engagement and acceptance.

In this study, we explore the impact of emotions, sentiments, the semantic brand score (SBS), and semantic product score (SPS) derived from consumer discussions on product videos on a product launch. Using these metrics, we develop a Product Launch Score (PLS) to assess the effectiveness of new product launch videos. The overall research process is depicted in Figure 1. Formally stated, this research aims to answer the following questions:

- RQ1: How be the discussions around newly launched products quantified to determine relationships and connectivity around products within comments?

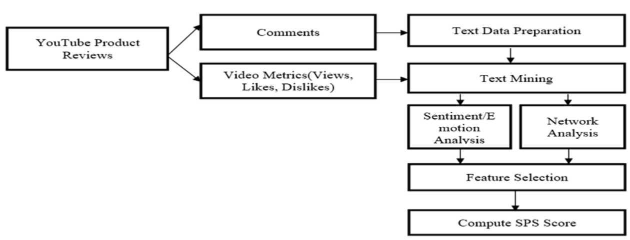

FIGURE 1. Research approach to proposed.

- RQ2: What are the different aspects of user generated contents (UGC) that can be quantified to derive a product launch score (PLS)?

This study can provide marketers and organization managers with a new KPI to evaluate the success of new product launch video campaigns. Moreover, the findings of this study provide insights into the type of emotion and sentiment the audience indicates during a new product launch.

II. LITERATURE REVIEW

A. COMMUNICATION CHANNEL

YouTube has become a critical component in strategic and social media marketing communication, particularly for targeting people aged 18–32 years [24]. Although YouTube marketing can influence this young target audience to some extent, it exerts a stronger effect on the general opinions and attitudes of youth [66]. Because YouTube is a crucial communication channel, various scholars have examined its effects across various disciplines [46]. A study reported that YouTube marketing communication leads to a favorable relationship between brand liking and brand preference [24]. Trustworthiness, social influence, and information involvement are significant factors affecting information credibility on YouTube [73]. Cartoons, memes or celebrity endorsements can be used for promotions [62]. In addition, marketers consider YouTube the most effective video ad platform [13], [56], and YouTube users are confronted with an ever-growing share of product promotions [54]. Product category and financial resources play a crucial role in the content marketing strategy on YouTube [68]. However, the promotional effectiveness and role of user emotions regarding product launch videos on YouTube remain unexplored.

B. YouTube AS A MARKETING COMMUNICATION CHANNEL

As of July 2021, YouTube has approximately 2.2 billion users and is projected to reach 2.8 billion by 2025 [36]. More than 500 hours of videos are uploaded to YouTube every minute [34]. YouTube is one of the first few sites that people think of while searching for a product's feedback. Most of the top 100 global brands use YouTube advertising as part of their marketing strategy to enhance their brand and company [25]. YouTube Ads not only enhance brand awareness and develop corporate brand image but also increases the purchase intention of YouTube users [27]. Engagement refers to the involvement, commitment, passion, enthusiasm, absorption, focused effort, zeal, dedication, and energy [64]. The engagement comprises behavioral aspects or click-based interactions (participation) as well as easy content viewing and reading (consumption) [26]. Social media has reinvented and improved the way people work [51]. Organizations recognize the value of engagement through their social media content [23]. The level of consumer engagement is higher when brand personalities such as humor and emotion are included in the content [23], the content leads to social interactions among users [21] and is rationally appealing [69]. The level of engagement differs among social media platforms. Clicking on "Like" or "Thumbs up" buttons is a simple engagement method [36]. YouTube users read comments for seeking information, like and dislike for entertainment, and comment for socialization. However, the effect of user engagement on product launch or promotional videos remains unclear.

C. EFFECT OF SOCIAL NETWORK

A social network enables people to stay connected with family, friends, colleagues, customers, acquaintances, or anyone with whom they wish to be in touch. The use of Internet-based social media has pushed the boundaries of social networks. People build and nurture social relationships even when they have no personal connections but a common social, business, or professional purpose. Thus, social media networks can be defined as a set of nodes tied to each other by one or more types of relationships [65]. Every social media platform has its primary purpose. For example, LinkedIn is primarily used to build professional relationships; Facebook is for personal connections; and

Twitter[1] primarily follows bit-sized stories from influencers, friends, and family. The underlying structure of these sites is to understand the virtual geographies of social networks by performing a comparative analysis of Facebook, LinkedIn, and A Small World [22]. Over the years, the analysis of social networks has provided a substantial amount of information. The Facebook social graph confirms the six degrees of separation phenomenon [65]. The Facebook social network users to find its effect on consumers' purchasing decisions [1]. A stronger correlation was observed between users' social popularity and their most popular content [2]. The concept of communities is slightly ambiguous in YouTube compared with other social media platforms such as Facebook, LinkedIn, and Twitter. Communities are formed by similar users, and no large similarity values exist between friends in YouTube communities [1]. Reference [42] reported that strangers, not friends or followers, play a crucial role in content propagation. Even if YouTube is not a brand community, it is conceivable because only a few social network participants create content [8]. The social network in YouTube influences to develop successful videos and guide opinion formation and direct product search and discovery [42]. UGC is responsible for forming networks. Comments, replies, and discussions are a producer of a plethora of information. Analysing this content can provide valuable insights into this digital world. In [20] Dogra et al. calculated the SBS from text data by combining social network and semantic analysis methods. However, no studies have examined social networks by using text data to understand consumer behaviour towards new product launches.

[1] After Elon Musk acquired Twitter, it was rebranded as X.

D. EFFECTS OF UGC

The UGC as the information that consumers generate and share on social media [15]. UGC can be in any form such as images, videos, text, and audio [52]. UGC is extensively used to understand consumer behavior. Researchers have indicated the importance of measuring customer satisfaction based on UGC by performing sentiment analysis [7]. The analysis of UGC can be helpful to determine prospective customers [4], propel customer-driven product design selection [37], and identify relationships between product features and consumer opinions [33], [63]. YouTube has billion hours of daily video consumption [45] and is a popular destination for digital video consumption [41]. It appeals to a diverse range of users and plays a crucial role in the emergence of UGC. User engagement on UGC in YouTube positively influences sales [14], purchase intention [15], and exerts a more substantial effect on customers' cognitive trust than marketing-generated content [19]. Millennials trust people over brands when making purchase decisions by watching various UGC on YouTube [43]. Studies have examined the relationship between attitudes towards UGC on YouTube and factors that affect the purchase intentions of products being reviewed [52]. Prior research on UGC related to videos has mainly focused on assessing video quality of user-generated content from both aesthetic and technical viewpoints [79]. This includes the development of RAPIQUE, which merges quality-conscious scene statistical features with semantics-informed deep convolutional features [80]. Additionally, studies involving the LIVE-YouTube-HFR database have explored the complex interplay between frame rate and perceived video quality [82]. Furthermore, advancements such as convolutional features and the Video Quality Evaluator (VIDEVAL) have been instrumental in achieving a harmonious balance between video quality assessment (VQA) performance and operational efficiency [81]. This literature review on UGC provides an opportunity to identify latent UGC-related factors that could be used to evaluate the success of launching a new product.

III. RESEARCH QUESTIONS (RQs) AND CONCEPTUAL HYPOTHESIS (H)

The literature review identified an opportunity to utilize UGC to derive a novel KPI for examining product acceptance and determining the product launch score (PLS). This score can be derived from analyzing different elements of feedback found in comments on product launch videos. Additionally, an endogenous relationship might exist among these aspects used to calculate the PLS. By reviewing previous studies, we found that when the content of a particular technology is satisfactory, the consumers (users) attempt to use that online service [11], and the quantity of posts exerts a positive influence on customer attitudes towards product content [6]. Accordingly, authors proposed the following hypotheses regarding product launch YouTube videos:

- H1: High volume of comments, likes and dislike would reflect on semantic product score (SPS). Accordingly,

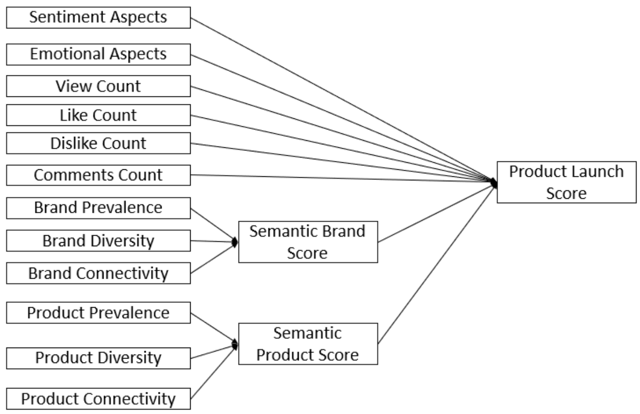

FIGURE 2. Product launch score model framework.

work demands to propose a model framework (Figure 2) using various aspects of the user generated framework in calculating the product launch score.

This study utilized both valence(sentiment) and arousal (emotional) aspects from UGC to calculate the PLS. The valence aspect measures whether the emotion is positive or negative, whereas the arousal aspect measures the intensity of the emotion [16], [32], [47]. Thus, a relationship might exist between sentiment and emotional aspects. In [17] Caballero et al. divided emotions into different dimensions, for example, trust and joy as high arousal positive emotions, whereas fear and anger as high negative arousal emotions. However, irrespective of the emotions, the brand might drive the volume of likes on the videos. On the basis on the previous studies, authors proposed the following hypotheses:

- H2(a): Low arousal emotions, such as sadness, would negatively affect the number of comments, likes, and dislikes in a product launch video.
- H2(b): Videos with high Semantic brand score (SBS) has more likes by the audience.

In another study [18], suggested that surprise elements in advertisements draw attention, promote positive attitudes toward the ads, and stimulate word of mouth. However, this study was based on a field experiment and survey. Moreover, we propose the following hypothesis on the user generated content of product launch videos.

- H3: A positive relationship between surprise emotion and product launch videos on a virtual platform such as YouTube would exist.

These hypotheses' results are essential to understanding and selecting important aspects to calculate the product launch score. In addition, this study also posited that SBS and SPS may have a positive association with PLS score.

- H4: SBS and SPS scores have a positive association with PLS scores

IV. RESEARCH METHODOLOGY

A. DATA COLLECTION

Data were collected by searching product launch videos by using the video search feature on the YouTube site. Data were randomly collected, and the video URL was used to extract data by using Google YouTube API V3. Videos having a minimum of 100 comments were extracted to ensure that the sentiment and emotional aspects are captured properly [48].

TABLE 1. Count of videos by organizations.

Company	Count	Company	Count
Amazon	1	Microsoft	2
Apple	4	Nike	1
Bajaj	1	Nokia	1
BMW	1	OnePlus	3
Canon	1	Oppo	2
Galaxy	1	PlayStation	2
Google	1	Realme	1
GoPro	3	Reliance	1
Honda	1	Samsung	3
Huawei	2	SONNY	1
Hyundai	3	Sony	3
Katrina	1	Tesla	2
Lenovo	1	Toyota	1
LG	2	Xbox	1
Mercedes	2	Xiaomi	2
Mi	1	-	-

Overall, 52 YouTube product launch videos having 1,11,716 comments were extracted for this experiment. Information regarding the following attributes was obtained using the YouTube data collection API: page views, likes, dislikes, and comments. The product launch videos corresponded to various companies spanning different business domains.

B. DATA PREPARATION

The most critical data for this experiment were comments or reviews on the product launch videos. Although all these texts can provide a substantial amount of information, they are not helpful in their original form. The proposed model filtered out nonessential information and retained only vital information and conducted text pre-processing to prepare it for analysis. The size of the feature space was reduced using various pre-processing methods. Techniques such as stop word removal, case folding, stemming, lemmatization, and contraction simplification were used to normalize the text. However, applying all normalization methods to the text is not necessary. It depends on the data and the type of analysis to be performed. The following pre-processing methods are used to prepare the product launch data for analysis [3]:

- Punctuation and whitespace removal: Whitespace and punctuation marks such as $+$, $-$, and $\sim$ were removed.
- Stop word removal: Stop words, such as common and short function words, were filtered to analyze the data effectively. The standard English stop word list Wordnet provided by NLTK was used to eliminate informal words. However, the stop word list provided in Wordnet includes words such as "not" which formed an essential part of our analysis. In the emotion analysis, words such as "not important" and "not needed" are vital for classifying emotion. Thus, the Wordnet was customized to exclude "not" from the stop wordlist.
- Text Normalisation: We can write words in various forms. Some words can be written in uppercase, lowercase, and multiple tenses. Thus, it is essential to convert all these words to a similar form for analysis and employed case-folding to convert all upper-case letters to lower-case letters. Subsequently, we used lemmatization to bring words to a base form. Lemmatization involves the morphological analysis of words to remove inflectional endings and returns the root form of the word known as a lemma. For example, working and worked are to work. We also removed numbers for comments. For text mining activities, numbers should be removed from the text. For instance, we can remove numbers when the task is related to sentiment or emotion analysis.

C. DATA ANALYSIS

To build multiple models to find the sentiment and emotions from product launch reviews. Sentiment analysis involves identifying the opinion of a person towards a particular entity. Let us take customer feedback as an example. Sentiment analysis of this text determines customers' attitudes toward the aspects of a service or product they describe in the text. Sentiment analysis has two aspects: subjectivity and polarity. The subjectivity of a sentence involves identifying subjective statements from data. Subjectivity ranges from 0 to 1, where 0 is very objective and 1 is highly subjective. The aim is to identify subjective opinions and classify them according to their polarity, namely positive, negative, and neutral. Polarity ranges from -1 to 1, where -1 is the negative sentiment and $+1$ denotes positive sentiment. For our analysis, we explored three sentiment analysis tools in Python: TextBlob, Polyglot, and SenticNet. Due to its limitations in recognizing abbreviations, Polyglot was deemed unsuitable for analyzing concise video comments and thus excluded from our study. Similarly, SenticNet was eliminated because it analyzes sentiments at the word level, not at the sentence level, which was required for our purposes. TextBlob, conversely, is built upon NLTK and Pattern, providing powerful optimizations and features ideal for a wide range of NLP tasks, which in turn enhances model efficacy [78]. Therefore, we chose TextBlob for conducting our sentiment analysis on the collected dataset. The text with a subjectivity score of >0.5 was considered for analysis because thoughts, feelings, or beliefs are expressed in these sentences. The overall sentiment for a product launch video was calculated as an average of polarity associated with comments. However, sentiment analysis summarizes an opinion at a macro-level and does not indicate the intensity of emotions expressed in the text.

Emotion analysis is a technique for identifying feelings expressed in text, enabling the detection of emotions like happiness, anger, surprise, sadness, and fear through specific detection methods. This approach is particularly useful in gauging audience reactions to new product launches by analyzing comments on launch videos. While sentiment analysis can reveal overall attitudes as positive or negative, emotion analysis delves deeper, identifying specific negative emotions such as anger, sadness, or fear. Fear may be a common reaction in product launch contexts, but anger or sadness signals potential issues. The Text2Emotion library is widely utilized in research for quantifying emotional expressions in texts [75], [76], [77]. Its applications include analyzing emotions in tweets about cryptocurrencies [76] and studying the impact of emotions expressed in tweets during the COVID-19 pandemic on stock prices [77]. These applications underscore Text2Emotion's effectiveness for studies like ours, where detecting emotional nuances from short text messages such as comments is crucial. We employed the Text2Emotion library in Python to analyze emotions in our dataset, leveraging its capability to identify emotion-indicative words, categorize each word's emotional tone, aggregate these emotions for overall text analysis, and further assess the Semantic Brand Score (SBS) based on the data.

The SBS measures the brand importance calculated from text data by combining social network and semantic analysis methods. In [74] Zhang and Luo used three measures, namely prevalence, diversity, and connectivity, to calculate the SBS. Prevalence measures the frequency of the use of the brand name, diversity measures the diversity of words associated with the brand, and connectivity represents the brand's ability to bridge connections between other words or groups of words. According to [31] and [48], the brand image creates customer experiences to purchase certain brands. Although the brand image is used to understand customers' opinions towards a brand, it is equally crucial for measuring the success of a new product launch.

The SBS methodology was modified to calculate the SPS. The SPS indicates the importance given to the category of the product being launched. Suppose people discuss the product and there is adequate diversity and connectivity within texts in a new launch video, then the video would raise awareness regarding the new launch within the targeted community. Thus, along with measuring brand influence from comments, measuring a new product's impact on prospective consumers is essential. This can be determined by how well the new product is perceived, the relevancy of the discussion, and the connectivity between conversations around the product. We extended the SBS to the SPS as follows:

- Product Prevalence: Prevalence measures the frequency of the use of the product, that is, the number of times the product is directly mentioned in comments.
- Product Diversity: Diversity measures the standardized diversity of words associated with the product. This is a measure derived from the degree of centrality measured in social network analysis studies. In a social network, degree centrality measures the total number of direct links with other nodes. When the product mentions cooccurring with many different words, this number tends to be higher.
- Product Connectivity: Connectivity represents the product's ability to bridge connections between other words or groups of words. Similar to product diversity, this measure is derived from the betweenness centrality measure in social network analysis studies. Betweenness centrality in a social network is a measure used to understand the importance of a node in transmitting information through a network [55]. A product mention with a high betweenness centrality is likely a central point of discussion in product launch videos.

The Pearson correlation method was used to determine if significant correlations exist between the different aspects of comments. This is essential to remove some of the highly correlated attributes and it helps in reducing the likelihood of the curse of dimensionality. The term curse of dimensionality was coined by Richard Bellman; it is a phenomenon observed while analyzing and organizing data in a high-dimensional space (Curse of dimensionality, Wikipedia). After the removal of highly correlated attributes, we analyzed all remaining factors. Linear regression analysis was performed to determine the correlation and directional relationship between attributes. This is a predictive analysis technique that helps describe the relationship between a dependent variable (interval or ratio) and one or more independent variables [70]. Furthermore, a PCA model for deriving the weights of each feature can be used for calculating the PLS. Generally, the supervised machine learning method is a more efficient method for determining weights or coefficients for features used in the model. However, the target or dependent feature is not available, the unsupervised technique PCA to calculate weights. PCA is a data reduction technique used to create one or more index variables from a larger set of variables. This technique involves a linear combination (weighted average) of a set of variables. These newly created index variables are known as components. Feature weights determined using the PCA model were used to calculate the PLS.

V. FINDINGS AND DISCUSSION COMMON MISTAKES

A. SENTIMENT AND EMOTION ANALYSIS

Overall, the sentiment expressed by users regarding product launches was positive (Table 2). Users expressed more positive sentiments than negative sentiments in all the product launch videos are analyzed (Figure 3). Positive sentiment in reviews exerts a positive impact, increases motivation [57], and demonstrates a positive relationship with the purchase intention of the product [30]. However, positive sentiment was associated with various high arousal emotions such as trust, joy, and surprise [39].

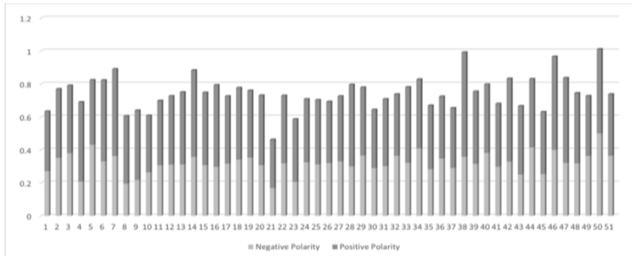

FIGURE 3. Sentiment polarities in videos.

TABLE 2. Average sentiment polarities of product launch videos.

NegativePolarity	43%
Positive Polarity	57%

The emotional analysis of data suggested that prospective consumers were more surprised while watching these videos (Figure 4). In [39] A. Lindgreen et al. described surprise as a highly efficient marketing tool and the emotion of surprise is required to attract new customers.

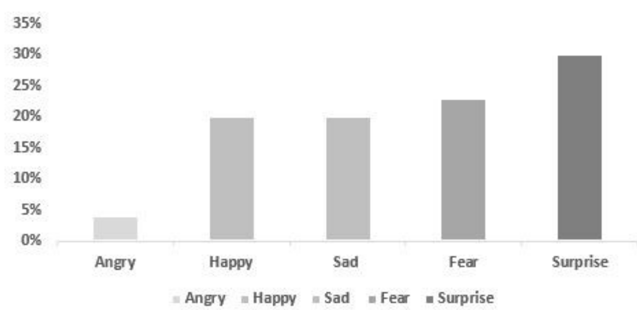

FIGURE 4. Emotion distribution.

Thus, presence of the surprise element in our data supports H3 and the surprise element can be used to calculate product launch score. Authors observed an element of fear in the reviews. However, some of the words used in the text2emotion Python library to identify fear, including confident, courageous, encouraged, passionate, and uneasy, can also be associated with surprise. A minor difference exists between the expression of surprise and fear words. Because

TABLE 3. Emotion distribution.

Happy	20%
Angry	4%
Surprise	30%
Sad	20%
Fear	23%

TABLE 4. Correlation matrix.

	Happy	Fear	Positive Polarity Mean	Negative Polarity Mean
Happy	1.00	−0.45	0.75	−0.23
Fear	−0.45	1.00	−0.57	0.33
Positive Polarity Mean	0.75	−0.57	1.00	−0.34
Negative Polarity Mean	−0.23	0.33	−0.34	1.00

TABLE 5. Effect of happy emotion on positive polarity.

Dependent Attribute:	Positive. Polarity			
Independent Attribute:	Happy			
Coefficients:				
	Estimate	Standard Error	t value	p value
Intercept	0.32	0.01	22.62	2.00E-16
Happy	0.54	0.06	8.2	6.98E-11
Residual Standard Error:	0.04			
R-Squared:	0.57			
Adjusted R-Squared:	0.56			
F-statistics:	67.31			
p-value:	6.98E-11			

TABLE 6. Effect of fear emotion on negative polarity.

Dependent Attribute:	Negative Polarity			
Independent Attribute:	Fear			
Coefficients:				
	Estimate	Standard Error	t value	p value
Intercept	0.4	0.03	12.22	2.00E-16
Fear	-0.34	0.13	-2.537	0.01
Residual Standard Error	0.05			
R-Squared	0.112			
Adjusted R-Squared	0.094			
F-statistics	6.43			
p-value	0.01			

TABLE 7. Effect of sad emotion on the count of likes.

Dependent Attribute:	Like Count			
Independent Attribute:	Sad			
Coefficients:				
	Estimate	Standard Error	t value	p value
Intercept	88016	34218	2.57	0.01
Sad	-306283	165387	-1.85	0.06
Residual Standard Error:	59320			
R-Squared:	0.06			
Adjusted R-Squared:	0.04			
F-statistics:	3.43			
p-value:	0.06			

we used this dictionary-based library to identify emotions, we examined the presence of two keywords, namely surprise and fear, in the text as a decent measure to represent the success of a product launch campaign and used them together for calculating the product launch score.

Positive emotions such as happiness help increase customer satisfaction, whereas negative emotions reflect the dissatisfaction of a user. As shown in Table 4, a high correlation was observed between positive polarity and happy emotions. Similarly, we observed a positive correlation between negative polarity and fear emotion. Moreover, the findings of regression analysis demonstrated these relationships (Table 5 and Table 6). Regression analysis indicated a significant relationship between positive sentiment and happy emotion (Table 5) and between negative sentiment and fear emotion (Table 6). Hence, to reduce the dimensions of data, selected the sentiment aspects, Positive Polarity Mean and Negative Polarity Mean, to calculate the product launch score.

When the audience does not like someone's video, they generally do not engage in any activity on the video. Few

TABLE 8. **Effect of sad emotion on the count of dislikes.**

Dependent Attribute:	Dislike Count			
Independent Attribute:	Sad			
Coefficients:				
	Estimate	Standard Error	t value	p value
Intercept	6817	2862	2.38	0.02
Sad	-27151	13833	-1.963	0.06
Residual Standard Error:	4962			
R-Squared:	0.07			
Adjusted R-Squared:	0.052			
F-statistics:	3.85			
p-value:	0.05			

TABLE 9. **Effect of sad emotion on the count of comments.**

Dependent Attribute:	Comment Count			
Independent Attribute:	Sad			
Coefficients:				
	Estimate	Standard Error	t value	p value
Intercept	7085	2904	2.43	0.01
Sad	-24722	14038	-1.761	0.08
Residual Standard Error:	5035			
R-Squared:	0.057			
Adjusted R-Squared:	0.03			
F-statistics:	2.101			
p-value:	0.08			

users comment or like/dislike the video. The results of Pearson correlation analysis revealed a negative correlation of the volume of likes, dislikes, and comments with sad emotion (Table 4). This finding indicated that sad emotion negatively influenced the number of comments, likes, and dislikes. However, the results of regression analysis indicated no significant relationship between these attributes (Table 7, Table 8, and Table 9). Thus, our results did not support H2(a).

B. SEMANTIC BRAND SCORE (SBS)

As shown in Table 13 and Table 14, indicates that almost all product launch videos in the top10 SBS list had more than 100K likes, whereas those in the bottom had less than 2K likes. Although the count of likes was not used as a factor

TABLE 10. **Correlation matrix.**

	Like Count	SBS Score	Comment Count
Like Count	1.00	0.93	0.98
SBS Score	0.93	1.00	0.94
Comment Count	0.98	0.94	1.00

TABLE 11. **Effect of the SBS scores on like count.**

Dependent Attribute:	Like Count			
Independent Attribute:	SBS Scores			
Coefficients:				
	Estimate	Standard Error	t value	p value
Intercept	2070.4	2008.8	1.031	0.31
SBS_Score	11.52	0.36	31.617	2.00E-16
Residual Standard Error:	13500			
R-Squared:	0.95			
Adjusted R-Squared:	0.95			
F-statistics:	99.6			
p-value:	2.20E-16			

TABLE 12. **Effect of the volume of comments on the SBS Score.**

Dependent Attribute:	SBS_ Score			
Independent Attribute:	Comment Count			
Coefficients:				
	Estimate	Standard Error	t value	p value
Intercept	-605.96	268.13	-2.26	0.03
Comment Count	0.92	0.04	19.1	2.00E-16
Residual Standard Error:	1802			
R-Squared:	0.87			
Adjusted R-Squared:	0.87			
F-statistics:	364.7			
p-value:	2.20E-16			

to calculate the SBS, the context of reviews and discussions around the brand on YouTube videos tended to affect the

TABLE 13. Top 10 videos with high SBS.

Brand	Video URL	Prevalence	Diversity	Connectivity	SBS
Xbox	https://www.youtube.com/watch?v=0 tUqIHwHDEc	81.93	69.81	63.89	215.63
Go-pro	https://www.youtube.com/watch?v=xYX6b1-9Coo	46.36	41.02	47.29	134.67
Go-pro	https://www.youtube.com/watch?v= Mh-x8kbJT5k	41.28	38.76	42.06	122.1
Tesla	https://www.youtube.com/watch?v=T b_Wn6K0uVs	37.66	34.88	41.79	114.33
Google	https://www.youtube.com/watch?v=r0iLfAV0pIg	37.3	39.34	31.71	108.35
Tesla	https://www.youtube.com/watch?v=Q4VGQPk2Dl8	34.37	30.78	29.86	95.01
Nokia	https://www.youtube.com/watch?v=T5JqxR_cPaw	29.15	31.98	26.4	87.53
One- plus	https://www.youtube.com/watch?v=E-51Kc42hoQ	29.92	28.79	28.64	87.35
Sony	https://www.youtube.com/watch?v=e0lLCqmHSSg	30.12	28.5	24.35	82.97

TABLE 14. Bottom 10 videos with low SBS.

Brand	Video URL	Prevalence	Diversity	Connectivity	SBS
SONNY	https://www.youtube.com/watch?v=K_w8z1OyOVA	0.22	0.47	-0.21	0.48
Hyundai	https://www.youtube.com/watch?v=F4OJqcYfptU	1.71	0.54	-0.27	1.98
Oppo	https://www.youtube.com/watch?v=4MlraYLE3fI	2	0.63	-0.09	2.54
Reliance	https://www.youtube.com/watch?v=JNFbR682wyA	2.39	1.02	0.48	3.89
Realme	https://www.youtube.com/watch?v=yzSjeHSchdc	1.46	1.7	2.32	5.48
Nike	https://www.youtube.com/watch?v=1D5zVxLSC_c	4.22	1.81	1.26	7.29
Galaxy	https://www.youtube.com/watch?v=ZGgFEk5Cvzk	4.9	4.79	0.3	9.99
Amazon	https://www.youtube.com/watch?v=OOwxoPdTN40	4.12	4.83	2.04	10.99
Apple	https://www.youtube.com/watch?v=IPvSAtAsMM4	4.35	4.07	3.56	11.98
Apple	https://www.youtube.com/watch?v=1tpU8cpgY1I	5.37	4.97	1.8	12.14

likability of the video. The authors observed a strong positive association between the count of likes and SBS score which is in accordance with hypothesis H2(b) (Table 11). In fact, there is a focus on increasing the volume of online posting and the richness of information generated by users around the brand attracts more users and increases the SBS Score (Table 12).

TABLE 15. Correlation Matrix: SPS score and count of comments.

	PREVALENCE	DIVERSITY	CONNECTIVITY	SPS	COUNT OF COMMENTS
PREVALENCE	1.00	0.78	0.77	1.00	0.96
DIVERSITY	0.78	1.00	0.95	0.79	0.76
CONNECTIVITY	0.77	0.95	1.00	0.78	0.71
SPS	1.00	0.79	0.78	1.00	0.96
COUNT OF COMMENTS	0.96	0.76	0.71	0.96	1.00

TABLE 16. Effect of the count of comments on the SPS.

DEPENDENT ATTRIBUTE:	SPS_SCORE			
INDEPENDENT ATTRIBUTE:	COMMENT COUNT			
COEFFICIENTS:				
	ESTIMATE	STANDARD ERROR	T VALUE	P VALUE
INTERCEPT	-78.24	37.49	-2.087	0.04
COMMENT COUNT	0.16	0.006	24.78	2.00E-16
RESIDUAL STANDARD ERROR:	252			
R-SQUARED:	0.92			
ADJUSTED R-SQUARED:	0.92			
F-STATISTICS:	614.4			
P-VALUE:	2.20E-16			

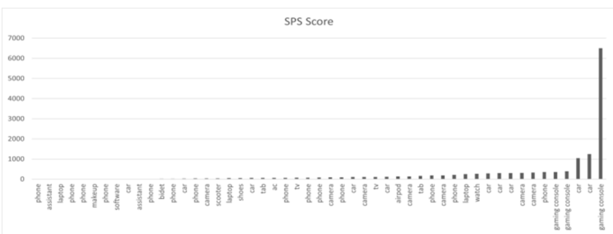

FIGURE 5. SPS for the videos.

This finding is in line with that reported by Colladon et al. [29] that increasing the volume of online posting is crucial to increasing museum visitors. The results of the Pearson correlation analysis of the volume of comments, likes, and dislikes (Table 10) revealed a high positive correlation between these attributes.

C. SEMANTIC PRODUCT SCORE (SPS)

The videos with a high SPS (Table 17) indicated that the audience was interested in seeking information and soliciting questions regarding the new launch. A previous study on UGC found that information seeking is a motive for social media use [38]. The SPS quantifies discussions around the product launch from comments. As shown in Table 15, a high correlation was observed between the volume of comments and the SPS. Although the count of comments was not used for calculating the SPS, it exerted a more significant effect on the frequency of brand or product mentions. We observed a significant relationship between the SPS and the count of

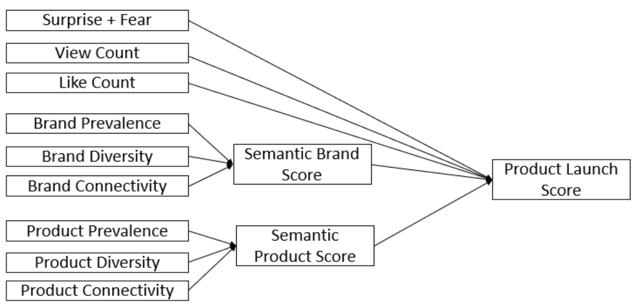

FIGURE 6. Product launch score model framework.

TABLE 17. Top 10 videos with high SPS.

Product	Video	Prevalence	Diversity	Connectivity	SPS
xbox	https://www.youtube.com/watch?v=0tUqIHwHDEc	6374	69.81323	63.89364	6507.707
car	https://www.youtube.com/watch?v=Tb_Wn6K0uVs	1201	31.0256	18.91904	1250.945
car	https://www.youtube.com/watch?v=Q4VGQPk2Dl8	965	35.71303	43.77302	1044.486
playstation	https://www.youtube.com/watch?v=cAEs3hI1f2w	372	13.43257	4.770438	390.203
playstation	https://www.youtube.com/watch?v=Jw8HCFZkBds	347	11.41116	2.707425	361.1186
phone	https://www.youtube.com/watch?v=T5JqxR_cPaw	315	24.23258	16.67221	355.9048
camera	https://www.youtube.com/watch?v=xYX6b1-9Coo	308	17.38394	4.648934	330.0329
camera	https://www.youtube.com/watch?v=Mh-x8kbJT5k	291	18.04137	4.906793	313.9482
car	https://www.youtube.com/watch?v=ZFjlzKDElkI	281	17.48898	7.435026	305.924
car	https://www.youtube.com/watch?v=2eBAGKpf8p8	250	27.51659	22.59585	300.1124

TABLE 18. Bottom 10 videos with a low SPS.

Product	Video	Prevalence	Diversity	Connectivity	SPS
phone	https://www.youtube.com/watch?v=yzSjeHSchdc	1	-0.24298264	-0.186060394	0.57095697
assistant	https://www.youtube.com/watch?v=OOwxoPdTN 40	1	-0.252970323	-0.135555116	0.61147456
laptop	https://www.youtube.com/watch?v=0offPzuu_7E	2	-0.22990717	-0.178671622	1.59142121
phone	https://www.youtube.com/watch?v=x0D-YApgt5I	3	-0.049683598	-0.192708744	2.75760766
phone	https://www.youtube.com/watch?v=4MlraYLE3fI	4	0.155460273	-0.381500304	3.77395997
makeup	https://www.youtube.com/watch?v=3F304hRV8C E	4	0.484434141	0.264014426	4.74844857
phone	https://www.youtube.com/watch?v=jAV37V7vEs U	6	0.085863636	-0.217919994	5.86794364
software	https://www.youtube.com/watch?v=9v73H8MY4I Q	6	0.050183403	-0.099541048	5.95064236
car	https://www.youtube.com/watch?v=F4OJqcYfptU	6	0.321731651	3.116679436	9.43841109
assistant	https://www.youtube.com/watch?v=r0iLfAV0pIg	12	0.019555133	-0.019077913	12.0004772

comments (Table 16). This finding indicated that YouTube videos with a high SPS had relevant discussions around the product, whereas users watching videos with a low SPS were not adequately engaged with the launched product. Thus, our findings support H1, which indicated that a high volume of comments would reflect the SPS.

The SPS, along with its metrics product prevalence, product diversity, and product connectivity, enabled us to understand the mentions regarding a product as well as the diversity and connectivity of newly launched products. However, the SPS did not provide insights into the geniality of the product. We can calculate the PLS by including the emotional and sentimental aspects to the equation. We considered the PLS as a combination of product sentiment and emotions, brand recognition, and newly launched product recognition. Until now, as discussed various aspects of online reviews in a product launch video on YouTube. In the next step, we removed unwanted features and calculated weights for attributes used for calculating the PLS.

D. ATTRIBUTE SELECTION AND PCA

Based on the results of feature exploration and hypothesis testing, we selected features that can be used for calculating the PLS effectively. Table 19 lists the selected features.

TABLE 19. Features for the PLS calculation.

Surprise Fear
View Count
Like Count
Negative polarity Mean
Positive polarity Mean
SBS
SPS

TABLE 20. PCA model.

PCA Parameters:				
Number of factors	1			
Rotate	Varimax			
Maximum tier	100			
Attributes	PA1	h2	u2	com
Surprise.Fear	0.12	0.01	0.98	1
viewCount	0.1	0.01	0.9	1
likeCount	1	1	-0.001	1
Negativepolarity Mean	0-.09	0.0086	0.99	1
Positivepolarity Mean	-0.09	0.0085	0.9915	1
SBS Score	7.80E-01	0.6	0.39	1
SPS Score	0.91	0.92	0.17	1
PA1				
SS loadings	2.48			
Proportion Var	0.35			
Mean item complexity	1			
Test of Hypothesis that 1 factor is sufficient				

Authors used all the selected attributes to calculate the PLS. However, not all attributes contributed equally to a product launch. Factors from the PCA model (Table 20) provided feature loadings that were used as feature weights.

As shown in Table 20, one factor was sufficient to derive the weights. We used the min–max normalisation to normalise the weight scale. The final normalised weights used for calculating the PLS are listed in Table 21.

VI. PRODUCT LAUNCH SCORE (PLS)

Using the factors and weights that are derived from our analysis (Table 21), The PLS is calculated as per Eq. (1).

$$\begin{aligned} \boldsymbol{PLS} = \boldsymbol{Log}(\mathbf{0.19} \times [\boldsymbol{Surprise} + \boldsymbol{Fear}] \\ + \mathbf{0.17} \times \boldsymbol{ViewCount} + \mathbf{1} \times \boldsymbol{LikeCount} \\ + \mathbf{0.80} \times \boldsymbol{SBS} + \mathbf{0.92} \times \boldsymbol{SPS} \end{aligned} \quad (1)$$

TABLE 21. Normalized feature weights.

	Weights	Normalised weights
Surprise + fear	0.12	0.19
View Count	0.1	0.17
Like Count	1	1.00
Negative polarity Mean	−0.09	0.00
Positive polarity Mean	−0.09	0.00
SBS	0.78	0.80
SPS	0.91	0.92

Logarithmic scales used to reduce the wide-ranging numbers to a small number, making it easier for comparing and interpreting results. Accordingly, we revise the proposed optimized model framework for computing product launch score as per Figure 6. By comparing Table 22 and Table 23, authors found that videos with a high product launch score were generally well-received by viewers. Videos with a low product launch score had relatively low emotions (surprise and fear scores), view and like counts, and poor SBS and SPS.

VII. THEORETICAL AND PRACTICAL IMPLICATIONS

The findings from this study have significant implications for future research and social media engagement metrics. From a theoretical standpoint, the study indicates that product launch videos with a high volume of comments had more likes and dislikes from users. However, low arousal emotions, such as sadness, did not affect the number of comments, likes, and dislikes in a product launch video. However, the audience (users) exhibits are more surprised when they watch the product launch videos. As examined by [71] videos with a surprise element attract prospects and new customers. This phenomenon is also observed in product launch videos, where the presence of intense emotions like a surprise is triggering better brand and product conversations. This finding adds to the growing LC4MP works of literature and serves as more evidence that the presence of intense emotions could lead to grabbing more attention towards the content. In addition, the SBS and SPS efficiently quantified discussions around brands and products in launch videos.

The findings in this study also suggest that the audience likes product launch content with more brand mentions. From a practical standpoint, content creators should always attempt to have a surprise element in their launch videos to drive more viewer engagement. Campaign managers should try to motivate initial viewers to comment to better drive further user engagement as it is observed that context of reviews and discussions around the brand in product videos tends to affect the likability of the video. The novel KPI Product Launch Score

TABLE 22. Top 10 videos with high PLS.

Company	Video Title	Video URL	Product Launch Score	Surprise	Fear	View Count	Like Count	Dis-like Count	SBS Score	SPS Score
Google	Meet Google Home	https://www.youtube.com/watch?v=r0iLfAV0pIg	6.87	0.29	0.16	249170572	17684	2576	108.35	12.00
Hyundai	Hyundai | The all-new i20 | Born Magnetic | Official TVC	https://www.youtube.com/watch?v=GAezmllazOI	5.99	0.26	0.25	32069450	3061	924	41.8	118.76
Xbox	Xbox Series X - World Premiere - 4K Trailer	https://www.youtube.com/watch?v=0tUqIHwHDEc	5.91	0.32	0.22	15990022	403405	37265	215.63	6507.71
Hyundai	Hyundai VENUE | The New Sport Trim and iMT | Connected to Excitement | Official TVC	https://www.youtube.com/watch?v=gBftFV8tQAQ	5.57	0.18	0.18	12191186	1210	303	43.74	61.92
Tesla	Model Y Unveil	https://www.youtube.com/watch?v=Tb_Wn6K0uVs	5.42	0.24	0.37	6165536	128452	3328	114.33	1250.94
Tesla	Tesla Unveils Model 3	https://www.youtube.com/watch?v=Q4VGQPk2Dl8	5.36	0.25	0.32	5636227	79774	1597	95.01	1044.49
Playstation	PlayStation 4 Launch | The PS4 Launch Video	https://www.youtube.com/watch?v=Jw8HCFZkBds	5.21	0.41	0.17	4240651	77241	2084	23.57	361.12
Gopro	GoPro: Introducing HERO8 Black Beyond Next Level	https://www.youtube.com/watch?v=Mh-x8kbJT5k	5.20	0.33	0.25	3844389	104544	1394	122.1	313.95
BMW	The all-new BMW 7 Series. Official launch film.	https://www.youtube.com/watch?v=2eBAGKpf8p8	5.18	0.3	0.22	4497971	23358	847	74.33	300.11
Gopro	GoPro: Introducing HERO9 Black More Everything	https://www.youtube.com/watch?v=xYX6b1-9Coo	5.14	0.33	0.25	3082462	112739	3013	134.67	330.03

TABLE 23. Bottom 10 videos with low PLS scores.

Company	Video Title	Video URL	Pro-duct Launch Score	Sur-prise	Fear	view Count	like Count	Dis-like Count	SBS Score	SPS Score
Nykaa	Katrina Kaif Own Brand KaybyKatrina Launched | COMPLETE EVENT | Nykaa #makeupthatkares	https://www.youtube.com/watch?v=3F304hRV8CE	3.16	0.15	0.13	35602	757	37	24.71	4.75
Huawei	HUAWEI Seamless AI Life Product Launch - Highlights	https://www.youtube.com/watch?v=x0D-YApgt5I	3.31	0.28	0.13	51090	1370	39	40.25	2.76
Mi	2016 Mi Max & MIUI 8 Product Launch Event	https://www.youtube.com/watch?v=jAV37V7vEsU	3.41	0.27	0.22	72738	515	23	41.17	5.87
Sony	Product announcement | Vlog camera ZV-1 | Sony	https://www.youtube.com/watch?v=5xRG3RaI9uE	3.52	e	0.29	49579	1590	42	43.5	40.16
Realme	Meet The Pro Trendsetters | Launch Event	https://www.youtube.com/watch?v=yzSjeHSchdc	3.63	0.4	0.08	82555	5918	376	5.48	0.57
SONNY	SONNY Launch Video	https://www.youtube.com/watch?v=K_w8z1OyOVA	3.68	0.23	0.29	133545	325	37	0.48	20.60
Lenovo	Lenovo ThinkPad X1 Launch Event 2020	https://www.youtube.com/watch?v=BssxA3iYGYc	3.74	0.23	0.28	106780	1741	72	42.28	53.14
Apple	Apple iPad Pro and Macbook Air event 2018 in under 12 minutes	https://www.youtube.com/watch?v=0offPzuu_7E	3.80	0.27	0.24	189840	1632	110	44.97	1.59
Hyundai	2020 Hyundai Creta Launched by Shahrukh Khan with Crazy Dance Moment| Full Speech&Event Video	https://www.youtube.com/watch?v=F4OJqcYfptU	3.80	0.3	0.23	179129	2000	126	1.98	9.44
Oppo	OPPO Reno3 Pro | Launch Event	https://www.youtube.com/watch?v=4MlraYLE3fI	3.84	0.55	0.17	197766	2950	336	2.54	3.77

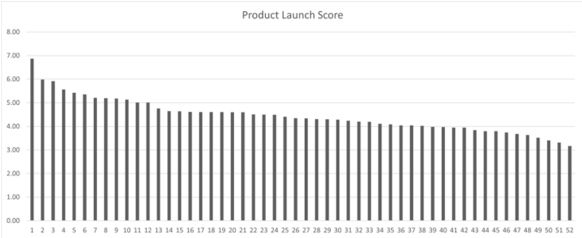

FIGURE 7. **Product launch scores comparison.**

formulated by the authors quantifies various aspects of UGC in a video to measure the performance of a product launch. This study adds to the growing social media marketing literature by providing a holistic KPI that aids in investigating various aspects that drive product and consumer success.

From a practical implication standpoint, this literature provides the digital marketing executives, campaign managers, and marketing analytics teams with a KPI that drives improved marketing strategies. Organizations use various tools to measure the promotional effectiveness of a product. Nevertheless, the need for a holistic digital marketing KPI for product launch videos has grown more as the world is undergoing a dramatic transformation [72]. The PLS score is crucial for learning from past launch experiences, providing a quick assessment of their success, and pinpointing areas of improvement for application in future campaigns. Leveraging PLS scores can significantly streamline the process of sifting through numerous metrics related to brand and product reception, facilitating a more efficient evaluation of digital video campaign performance.

Additionally, this KPI aids in measuring the performance of a product launch over time and comparing it with competitor launch videos. By analyzing the metric over time, marketing teams can gain a more holistic understanding of how well their product launch is resonating with consumers and where improvements can be made. This data-driven approach allows for more informed decision-making and can help drive future marketing strategies. Ultimately, the product launch score provides valuable insights that can lead to increased brand and product loyalty.

Campaign managers and marketing teams can employ this KPI to evaluate and choose the most effective product launch video for additional promotion, as shown in Figure 7. The significance of brand and product-related discussions is crucial in influencing consumer preference towards the product. The study's results reveal the engagement level of viewers with new product launches through these videos, showing that viewers tend to react positively to product launches. Nonetheless, incorporating an element of surprise in these videos is essential for captivating the audience's interest in the product and brand.

VIII. CONCLUSION AND FUTURE SCOPE

In this paper, we presented a novel KPI, PLS, considering the UGC data from the product launch videos on YouTube. Authors discovered surprise emotion dominantly being reflected in majority of the user comments on product launch videos. We proposed the method to calculate PLS using appropriate methods to clean the noisy user comments data. Then, various sentiment and emotion aspects were computed, followed by calculating SBS and SPS metrics. Finally, feature reduction was performed considering the correlation between these aspects, and feature weights were computed to calculate the PLS score. The proposed score can be used as a KPI to measure the promotional effectiveness of new products.

This study has some limitations that should be addressed. The current study focused on UGC such as comments, views, likes, and dislikes. Following are some of the limitations and areas which future studies might consider. Future studies should understand the motivation of users who produced or watched UGC. It is necessary to identify fake reviews that might skew the PLS calculation and mislead marketers. Fake reviews are false, bogus, and deceptive reviews and are inconsistent with an honest evaluation of products or services [40]. Similarly, there are situations where sentences are loaded with sarcasm, which mockingly praises a product while ridiculing it [5]. Detecting sarcasm in a viewer's comment can help reduce the incorrect classification of the viewer's sentiment towards the product launch. Lexicon-based sentiment and emotion analyses were performed in this study. This analysis can be improved further by utilizing deep neural networks or other advanced techniques [58], [59].

Furthermore, from a marketing viewpoint, new launch videos from social media platforms such as Instagram can be analyzed for additional insights. Additionally, analyzing live stream videos is valuable since the audience engages directly with the product launch. Future research should include additional variables like the duration of product launch videos, as there could be a connection between viewer's attention span and the video length. While this study exclusively examined user-generated content (UGC), incorporating an analysis of marketing-generated content (MGC) alongside UGC may offer new insights.

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