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Social media metrics and sentiment analysis to evaluate the effectiveness of social media posts

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Abstract

The present paper presents the results of an analysis of indicators underlying successful self-marketing techniques on social media. The participants included YouTube gamers. We focus on the content of their communication on Facebook to identify significant differences in terms of their user-generated Facebook metrics and commentary sentiments. Methodologically, ANOVA and sentiment analysis were applied. ANOVA of the classified post categories revealed that re-posted YouTube videos gained significantly fewer likes, comments, and shares from the audience. On the other hand, photos tended to show significantly more follower-generated actions compared to other post types in the sample. Sentiment analysis revealed underlying follower negativity when user-generated activity tended to be relatively low, offering valuable complementary results to the mere analysis of other post indicators, such as the number of likes, comments, and shares. The results indicated the necessity to utilize natural language processing techniques to optimize brand communication on social media and highlighted the importance of considering the opinion of the masses for better understanding of consumer feedback.

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Keywords: social media metrics; self-marketing; sentiment analysis

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1. Introduction

The emergence of the Web 2.0 era and the birth of social networks opened a unique opportunity for individuals' self-representation and self-expression[1]. YouTube became the market leader in video content sharing, and it did so by providing content creators with tools and self-marketing techniques[2] that allowed them to successfully gain monetary profits from viewing their content as well as possible worldwide recognition[3,4,5].

The birth of YouTube gaming and the increasing popularity of gaming channel owners have encouraged scientific researchers to conduct in-depth studies on the characteristics of self-marketing communication and its effectiveness, that is, on the content forms that grab user attention and those that lead to lack of follower activity. Thus, the present quantitative exploratory study introduces an approach to measure communication effectiveness of YouTube gamers by analyzing the content posted on their Facebook brand pages.

The goal of this paper is to identify the relationship of these content types with user-generated metrics on Facebook, such as the number of likes, comments, and shares, complementing these results with sentiment analysis of commentaries appearing below the sampled posts.

The results of this paper provide valuable information that may be utilized by self-marketed individuals or companies to better optimize brand communication on social media. Furthermore, by using this approach, independent game developers and actors of the ever-growing gaming industry can gain valuable insights about their customers' feedback for the enhancement of their future products.

2. Literature Review

The discussion and research on self-marketing as a form of advertising that applies traditional branding techniques to human beings[1, 5], began at the end of the 20th century[6]. Researchers are still discussing the terminology of this phenomenon. Terms such as „personal branding," „personal marketing," and „self-marketing" have been used interchangeably[2]. Individuals as actors of this phenomenon are referred to as „human brands," „branded individuals," and „branded personas"[2,7]. The extant literature in this domain focusses on the process of personal branding[2,4,8,5] and aims to determine the underlying factors of success by branded persons.

Studies discussing the importance and role of sociocultural background in fruitful personal branding[2,8,5] considered Bourdieu's field-theory[9] and theses about the forms of capital[10]. YouTube functions as an organized field where YouTube gamers are actors (referred to as agents by Bourdieu[9], each of whom hold cultural capital in the form of their educational qualifications and social capital defined by their acquaintances and social networks)[9]. Each channel owner has a unique habitus[9] as well, which consists of attitudes and behavioral characteristics that are crucial to their self-representation, for example, in their YouTube videos.

YouTube gamers have been gaining in popularity[1,5] in the last decade, and studies have pointed out numerous benefits of social media data analysis[11], indicating that the analysis of user-generated text commentary, or the online opinion-mining of the masses, has become one of the most pressing issues[12, 13].

The prediction of box office revenues for future movies[14] and election outcomes[15] became widely used applications of sentiment analysis. However, due to the relative infancy of this research domain, the determination of the most suitable methodology is still a subject of discussion among scientists.

We support the recently emerging studies that have argued for the complementary usage of sentiment analysis of social media[13] along with its "traditional" retrievable metrics (i.e., number of likes, comments, shares of posted contents) to achieve a deeper understanding of audience reactions to communication forms of self-marketing on social media.

3. Method

The sampling and data collection methods as well as a classification of the retrieved posts and data analyses are presented in the following subsections.

3.1. Sampling

YouTube gamers, namely PewDiePie, Markiplier, and Kwebbelkop, were chosen as units of analysis in the first stage of sampling. The chosen gamers can be considered a judgement sample because they share common characteristics, specifically, often playing the same games, being in the top 100 most popular gaming channels, and frequently using Facebook as a means of communication. Furthermore, they were part of Revelmode, a sub-network of Maker Studios that featured PewDiePie and his YouTube gaming friends.

Criterion sampling was used during the second stage of sampling[16]. The same number of posts (n = 50) with the same end point on the sampling time scale were established to allow for comparisons among the sampled YouTubers.

Lastly, in the third sampling stage, all comments appearing under the sampled posts were retrieved for future sentiment analysis purposes.

3.2. Data collection

Netvizz, an integrated Facebook application[17], was used to extract 50 posts from each of the pages of the sampled YouTubers and their Facebook metrics, along with all comments on those posts with timestamps.

3.3. Classification of posts

We used a Grounded Theory approach to classify the 150 retrieved posts[18].

Open coding consisted of core categorization of the retrieved posts into four core categories: link, photo, status update, and video.

During axial coding, the previously generated core categories were revised. As a result, the core category "video" was divided into two segments: "integrated Facebook videos" that were made explicitly for the Facebook audience and "embedded YouTube videos" that first appeared on YouTube and were later reposted on Facebook.

After successful determination of core categories, the sampled posts were further classified into subcategories according to their content during the phase of selective coding. Following the steps of Grounded Theory, these subcategories were subservient to the previously generated core categories[18].

3.4. Data analysis methods

Following a univariate analysis of Facebook metrics, ANOVA was used to test for possible significant differences among the classified post categories in terms of their Facebook metrics. Kolmogorov-Smirnov tests were used to decide between nonparametric and parametric analysis approaches. As a result, Kruskal-Wallis H tests were conducted along with Dunn's post-hoc pairwise comparisons[19].

The supervised learning method "k nearest neighbor" (often abbreviated as *k*-nn) was chosen for the sentiment classification of the retrieved commentaries. Due to the rare existence of neutrality regarding comment sentiments on social media[20,21], a bivariate training set, consisting of an equal number of hand-labeled positive and negative commentaries was used. This set was "trained" on the test data (i.e., the remaining comments), where machine-based classification was performed according to the rules that the computer "learned" from the training set[12,22].

The aforementioned *k*-nn approach predicted the sentiment score of a test data item according to its similarities to a previously-tagged training set items. The sentiment score was determined in the same manner as the training set item that was most comparable to it, using the most similar word patterns[22]. The analysis was performed with varying amounts of nearest neighbors (i.e., closest matching items of the training set) to achieve the most accurate prediction of the test data items[22]. For this reason, we also tested accuracy with alternative numbers of positive and negative training set items (N = 100; N = 200; N = 400). The process was conducted using the educational license of RapidMiner Studio 7.5[23], which is a code-free environment for designing advanced analytic processes with machine learning, data mining, text mining, predictive analytics, and business analytics.

Similar to the Facebook metrics analysis, Kruskal-Wallis H tests with Dunn's post-hoc pairwise comparisons were used to determine possible significant differences among the sentiment score means of the distinct post categories.

The results of the Facebook metrics and sentiment analysis were compared in the last step of the data evaluation to reveal similarities and differences.

4. Results

4.1. Facebook metrics analysis

The core category classification of the sampled posts showed distinctive differences. Kwebbelkop posted almost exclusively photos while PewDiePie and Markiplier posted mostly reposts of their previously published YouTube videos.

Significant differences in core post categories and their Facebook metrics were detected between like, reaction, and total engagement scores of all three YouTubers analyzed. However, regarding shares, only Markiplier's sample showed significant differences in the core categories of his sampled posts. Differences in the means of Kwebbelkop's comment scores were also non-significant. Figure 1 summarizes the rank orders of the classified core categories by the sampled YouTubers where significant differences were observable. (The figure uses numeric differentiation for the representation of the classified post types: 1 – link; 2 – photo; 3 – status update; 4 – integrated Facebook video; 5 – embedded YouTube video).

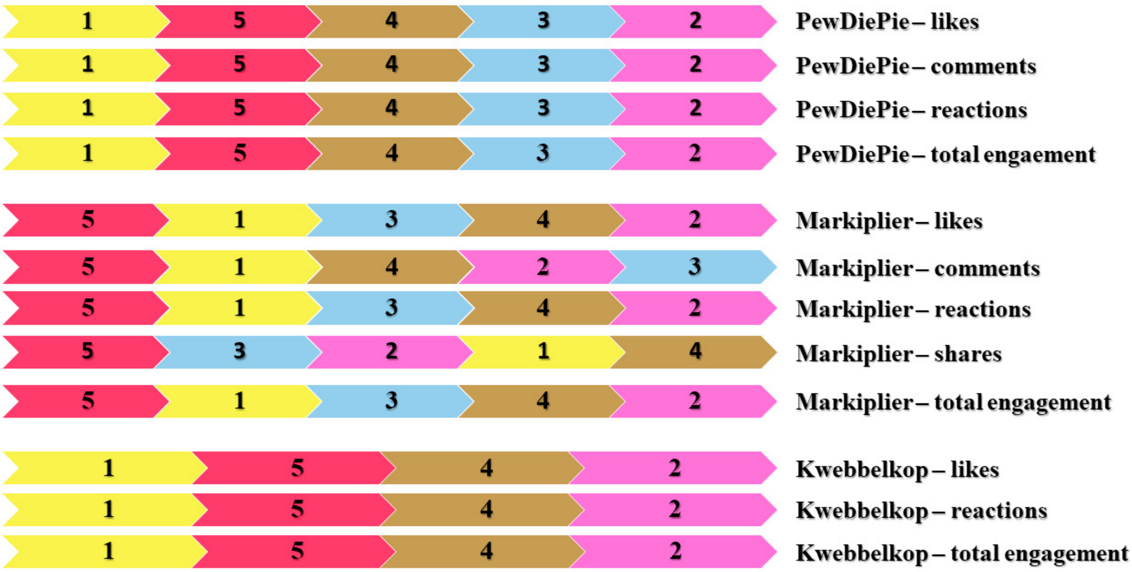

Fig. 1. Core category median rankings of the analysed Facebook metrics by the sampled YouTubers

The ANOVA results of the core post categories and their Facebook metrics revealed that links tended to receive significantly fewer user interactions than did photos. The same patterns were observed in the case of embedded YouTube videos. This core category also received significantly less user interaction by all measured Facebook metrics than did photos. These results are especially interesting in the light of previously discussed ratios of sampled posts in different core categories. In the cases of Markiplier and PewDiePie, the number of reposted YouTube videos was larger compared to any other core post categories. However, their shared photos received significantly more user-generated interactions. These highly-engaging photo posts accounted for 34% of posts sampled from Markiplier's page, whereas PewDiePie's sample contained only two photos, in spite of their excessive popularity among his followers.

The ANOVA of post subcategories and their Facebook metric means demonstrated that photos depicting the *family, friends, pets and/or the YouTubers themselves* received significantly more user-generated actions compared to subcategories with the lowest means in the sample. Furthermore, posts encouraging *audience interaction* and engagement (i.e., give an opinion, “like” if they agree etc.) received significantly higher Facebook metric means compared to lower-ranking subcategories.

As Fig. 2 illustrates, the rank orders in terms of their share and comment means changed significantly. The figure uses the same metric system for the subcategory visualization as in Fig, (the first number represents the core post category, whereas the second number refers to the subcategory of this particular core category). As an example, in the case of Markiplier, some posts discussed problems regarding YouTube and the gamer community (i.e., the subcategory numbered “15”). As it can be seen from the figure below, this subcategory reached outstanding results regarding their “share” metrics and also ranked higher in the number of comments it gained than regarding its “likes” or even “total engagement” scores. The “k nearest neighbor” sentiment analysis of user commentaries can give valuable insights into the reasons why these posts were widely shared and commented, although they did not gain an extensive number of likes.

Fig. 2. Subcategory median rankings of the analysed Facebook metrics by the sampled YouTubers

4.2. Sentiment analysis

The accuracy analysis showed that the highest accuracy (82,3%) was achieved with the training set containing 200 positive and 200 negative comments, using $k = 1$ nearest neighbors.

After the successful sentiment classification, Kruskal-Wallis H tests were conducted. Significant differences in the mean sentiment scores of both core and subcategories of the retrieved posts were detected for all three YouTubers.

Embedded YouTube videos tended to gain significantly less positivity in their sentiment means throughout the sample compared to any other core categories. In comparison to other content types, the ratio of negative commentaries submitted for this post category was relatively high.

In contrast to re-posted YouTube videos, photos tended to receive significantly more positive sentiments compared to other core categories for all three gamers by reaching the highest ratio of positive commentaries in the samples.

The subcategory sentiment analysis revealed that although likes for certain categories had relatively low means, they "jumped" to the top-ranking places in terms of their positivity means. The aforementioned discussion of commentary regarding YouTube problems and other events that shook the gaming community during the sampling time had a high effect on user commentary sentiments, where fans tended to lend their support regarding these discussed issues.

4.3. Comparison of Facebook metrics and sentiment analyses

Based on the analysis of similarities and differences regarding Facebook metrics and sentiment mean rankings, it can be concluded that the observation of commentary sentiments had a complementary function in the understanding of content popularity.

Considering photos, although sentiment positivity underlined the preliminary Facebook metrics results and showed that posts in this core category do not merely receive a large number of user-generated actions, they also stimulated positive written opinions. However, in particular cases, sentiment analysis revealed hidden feedback negativity and/or possible debates in the comment sections.

Sentiment analysis shed light on certain game-related negative user feedback as well as enormous positivity among subcategories that did not receive popularity according to their Facebook metrics.

5. Conclusion

The results of this study suggest the importance of not relying on and utilizing solely retrievable user-generated metrics. Instead, the sentiment of the text commentary accompanying social media posts should also be incorporated in the analysis.

Even though the core content form on Facebook consisted of reposted YouTube videos by PewDiePie and Markiplier, the relative lack of user activity paired with a high ratio of negative user commentaries called into question such a communication strategy. However, photos, especially those showing friends, family, pets, and the YouTube gamers themselves, resulted in the highest user activity and positive comment ratios.

Sentiment analysis of Facebook metrics revealed the unpopularity of certain content and underlying fan debates and disagreements with the gamers' opinions about frequently discussed issues. Machine-learning based sentiment analysis proved to be capable of analyzing hundreds and thousands of commentaries accompanying a single posted comment.

The combined analysis of user-generated metrics and sentiment classification provides information that is necessary for self-marketed individuals to optimize their communication on social media, which plays an important role in achieving a steady audience growth that can result in monetary profits as well. The application of these techniques allows independent game developers and the gaming industry as a whole to gain insights into the critical reception of their products from the target group itself. In consideration of the steadily growing global phenomenon of social media marketing and growing number of companies with diverse products and services targeting potential consumers on various social media platforms, the authors of this paper believe that both user-generated metrics analysis and sentiment mining are of essential importance for marketers of the contemporary era.

Future studies should clarify the weights and roles of the communication effectiveness indicators used in this research project utilizing a larger sample and possibly stepping out the domain of YouTube gamer brand personalities. This will help to improve the study of brand personality communication on social media, regardless of the domain in which these persons are active.

Recent studies on behavioral motivations in social media engagement have shown the importance of the uses and gratification theory[24, 25] and social exchange theory[26, 27] for the deeper understanding of factors that influence users to share, like, or comment on social media posts. The parallel investigation of user motivational factors combined with the presently described post classification method, Facebook metrics analysis, and sentiment-mining technique can help determine possible motivational differences in user engagement in the analyzed post types. Further research should clarify the possible interrelationships between underlying behavioral dimensions and the extent of user engagement in terms of different post types and examine their relevance from economic, social psychological, and marketing aspects.

This approach used the supervised learning method of sentiment analysis, *k*-nn. Although the test can predict the commentary sentiments with 82.3% accuracy, their possible review using other techniques (e.g., Naïve Bayes, Support Vector Machine (SVM), or sentiment dictionaries such as SentiWordNet) would add further insights into the present findings.

We hope that the results discussed will contribute to the body of knowledge in the field of social media communication among self-marketed individuals and also provide valuable insights for gaming industry actors and social media marketing research professionals.

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