Predicting factors to get maximum social media engagement of customers for brand building

Fiza Khan[1], Zahra Hafeez[2], Aimen Ijaz[3], Maryam yousuf[4], Reda Shaheen[5]

Department of computer science, National Textile University Faisalabad, Pakistan

fizakhan7878@yahoo.com[1], zahrahafeez668@gmail.com[2], aimenijaz906@gmail.com[3] maryamyousaf1158@gmail.com[4], redashaheen66@gmail.com[5]

Abstract— **Social media is an interactive platform on the internet which can be used to gain the attention of customers as social media users are increasing daily. This paper presents the factors that can get maximum interactions of the customers through the brand's posts on Facebook which will help advertising managers for making decisions. We used a data mining approach to predict the social media performance of a cosmetic brand. 500 publications of the brand were modeled and an output performance metric 'total interactions' showing the engagement of customers with the post, calculated by summing up three other metrices including likes, shares and comments was assessed and effects of input metrices on it was observed to provide an idea to advertisers of how to publish the posts. Post time, day and month were focused to target the cognitive and emotional senses of the customers. It was observed from results that people are more cognitively affected by photo type posts, and they were emotionally active at night time, weekends and at the start of the year.**

Keywords— Social media, brand building, facebook, advertisement.

I. INTRODUCTION

Social media has become a platform for the advertisement of brands. Advertising agents and marketers are focusing on getting more customers and sale through social media. We see adds of different brands on YouTube, Facebook, and other social networking sites and sometimes questionnaire about the brand's advertisement, these all are the techniques of marketers to get maximum customers and active participation of the customers on their pages for a good impact on other viewers of products through social media. A study of factors determining social media on cosmetic brand revealed that business today is changing from a transactional relationship to a social relationship and social media marketing leads cosmetic brands to reach regular customers of brands who grab the products of their demand [1]. According to Statista Dossier Facebook has 2.27 billion monthly active users making it an active platform for the brand building. Advertising experts are continuously trying to achieve customer engagement and trust in the product through online branding as it involves less workforce, budget and time. Facebook also calculates daily engagement of customers by adding likes, comments and shares and dividing it with the total fans of the page which gives an idea that getting a maximum number of these three attributes will help in brand building. Targeting the cognitive and sensory experience of consumers can help in achieving it.

Targeting the emotions of the consumers can help in brand building [2] who used two Facebook brand pages, French and Saudi Arabia belonging to a French beauty and cosmetic company. Analysis of consumer behavior towards cultural and international posts on pages revealed that people are intrigued emotionally with culturespecific posts which gave us the idea that targeting the emotions of the consumers can help in getting maximum response from them on the pages, i.e. likes and comments so we tried to target the emotions and cognitive senses of consumers by analyzing the attributes like post time, day and month given in our used dataset. We extended the work done by [3] who used 790 Facebook publications of a same cosmetic company and analyzed the metric "LifeTime Post Consumer" in detail as it had least mean absolute percentage error and through regression analysis described the influence of input attributes on it.

This paper is organized as follows. Section 2 presents state-ofthe-art research work on brand building through social media. Section 3 presents our methodology and experiments; Results and analysis are shown in section 4, and section 5 presents the conclusion.

II. LITERATURE REVIEW

Reference [4] in his research of Conceptualizing and evaluating experiences with brands on Facebook discussed two series of metrices "value of fan" based on people who claim that they are likely to do a social media action, i.e. like, comment or share along with purchase and "value of experience" based on people who claim that they will like to purchase. Considering the emotional statement in data gathering he observed that 70% of people who claimed they experienced strong positive emotions while viewing the page were likely to post a positive comment about the product and 64% of the people who claimed that this made a strong impression on their visual senses were also likely to make a positive comment about the page and when people will have a positive impact they will prefer the brand. It is usually believed that getting maximum likes on the page will be good for the brand building, but researchers proved it wrong. Figure 1 is derived and made from the study of [4] by us to have an idea about how customers should be targeted [1].

If the customers are targeted cognitively sensitively and emotionally then most of them will be likely to do positive comments on the post, they may visit the site and buy the product as well. If they do like, comment or share and visit the site they belong to the value of fan metric, and if they buy something as well, they belong to the value of experience metric [2].

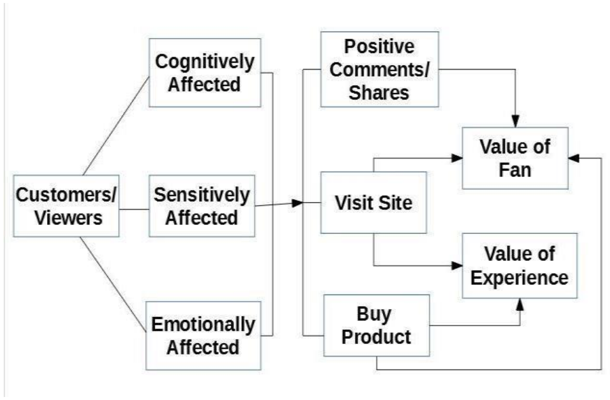

Figure 1: Impact of social media posts on customers

[5] in their research calculated the engagement rate using Facebook's engagement rate formula of 20 brand pages and revealed that brands having large fan base have relatively very low engagement rate and some brands having high engagement rate had very low fan base compared to others. [6] also analyzed the effects of attributes on output metrices using this same dataset that we are using and provided suggestions for advertisement. [7] while examining customers response to influencers advertising the brands, highlighted that trends of makeup change during different seasons. Social media has become a useful marketing tool [8] presented an empirical study on social media as a marketing tool. According to [8] among 150 respondents of research, Facebook was most popular social networking site, 46% people spend 2, 3 hours on these sites and 42% people considered social media for buying decisions. They observed that many fans come to the brand's page through advertising. Another research approach, i.e. hypothesis testing for Samsung home appliances was used by [9] who rejected the hypothesis that social media does not affect the consumer buying behavior indicating that these websites are an essential place for e-marketing. They also declared that Facebook has significant impact on brand building [3].

Viral marketing is an emerging branding strategy. [10] focused on practical implications of viral marketing over word of mouth. All studied companies preferred social media for marketing; these brands show their specialty and power to get consumer's readiness such as likes, comments, shares. Kept users up to date about their products and tried to build up the brand loyalty towards their products [4].

Social media is taking control over the world and companies took advantage of it, being interactive with users they get to know about consumer needs. Companies tried their best to create awareness of their brand through social media and build consumers trust by introducing new ideas, improving their product qualities [11]. The research of [3] that we extended tells us that as page total likes increases negative comments by users may cause the downfall in post consumers and brand sale and discussing post total consumers, they revealed that page total likes affected 17% among all other input metrices. They described that post type, i.e. photo, video, link status affected it most and among post, type status got most LifeTime Post Consumers which was is different from our analysis for Total interactions on a post. We checked how to get maximum interactions on the post and how input factors affect them. We related the input factors post time, day and month with vision and emotional senses of consumers [5].

III. Dataset And Methodology

We used the dataset collected from the posts published by a cosmetic company from 1 Jan to 31 Dec 2014. The input dataset consisted of 7 attributes, and the output metrics were 12. Researchers have worked on it and described the effects of input metrices on LifeTime Post consumers [3] which are the people who have clicked anywhere on the post. We focused on getting more total interactions on the post showing the positive attitude of customers on the product which will increase the chances of brand building. The seven input metrices are shown in **TABLE 1** and the impact of input metrics on output metric "total interaction" was observed in this study.

TABLE 1: INPUT METRICS OF DATASET, ADAPTED FROM [3]

Features	**Description**
Category	Action (Offers), Product (Advertisement of brand), Inspiration (Brand Related Content).
Page Total Likes	Sum of a number of people who have liked the page of the company.
Types	Type of posts (link, photo, status, video).
Post Month	(January, February, March, …, December) The month when the post was published
Post Hour	(0, 1, 2, 3, 4, …, 23) the hour when the post was published.
Post Weekdays	(Sunday, Monday, …, Saturday) the day of the week when the post was published.
paid	Either company paid to Facebook or not (Paid, Unpaid).

As we targeted people emotionally, so we tried to understand that which month, weekday and what time of the day gets us the most significant number of interactions from consumers TABLE 2 shows the output metrices. 'Total interactions' is calculated by summing up likes, shares, and comments by the viewers of the post. It is classified as the performance metric.

TABLE 2: OUTPUT METRICS OF DATASET, ADAPTED FROM [3]

Features	**Description**
LifeTime Post Total Reach	A total number of people who viewed the post (unique users).
LifeTime Post Total Impressions	A number of times a post from a page is displayed, whether it is clicked or not. People may see more than one impression of the same post. For instance, one may see a Page update in News feed once, and a second time when someone shares the same post.
LifeTime Engaged Users	Number of People who clicked anywhere on a post (unique users).
LifeTime Post Consumers	The number of people who clicked anywhere in a post.
LifeTime Post Consumptions	A number of clicks on a post (anywhere on the post).
LifeTime Post Impressions By People Who Have Liked A Page	A total number of impressions only by people who already liked the company's page.

LifeTime Post Reach By People Who Liked A Page	A number of people who viewed a company's page post because they liked that company's page (unique users).
LifeTime People Who Have Liked A Page And Engaged With A Post	A number of people who liked a Page and clicked anywhere on a post (Unique users).
Comments	Total comment on the post.
Likes	Total "Likes" on the post.
Shares	Total shares of the post.
Total Interactions	The sum of likes, comments, and shares of the post.

IV. Results And Discussion

As described that there were seven input attributes and effect of these input on output metric "total interaction" were observed in our research, we are describing them one by one. Figure 2 shows the effect of the month attribute on total interactions. In October, we got maximum interactions on cosmetics brand page, the least number of interactions were in January.

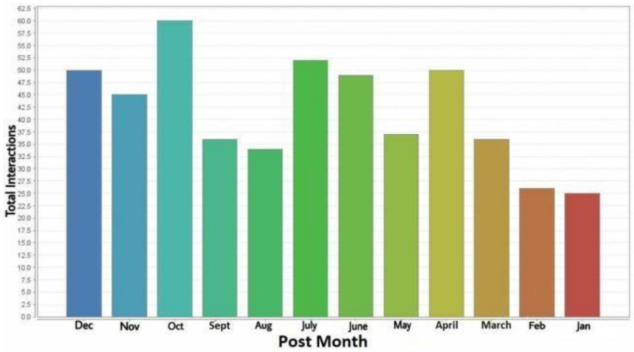

Figure 2: Impact of post month on total interactions.

Figure 3 shows the relation between weekday and total interactions. The maximum number of total interactions were collected on Saturday and Friday which describes that advertising manager should post on these days to get more likes and shares. People will be free during the weekends to scroll Facebook leading them to see our posts as well. It was observed that Monday has also received a remarkable number of interactive customers.

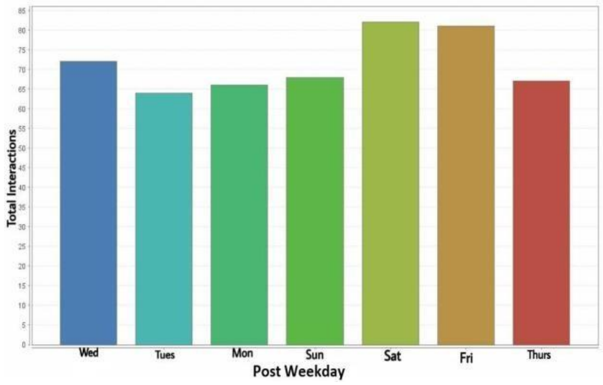

Figure 3: Impact of post weekday on total interactions

The photo value of the attribute Type got us maximum number of the user interactions with the post as shown in Figure 4 which means that maximum likes, shares and comments were on the photos posted by advertisers [3] in their research showed the status attribute gets more post consumers but we observed, to get more likes and comments one should post a photo. We can claim that photo affects viewers more cognitively and they prefer photos to share and comment over links which need to open in new browsers.

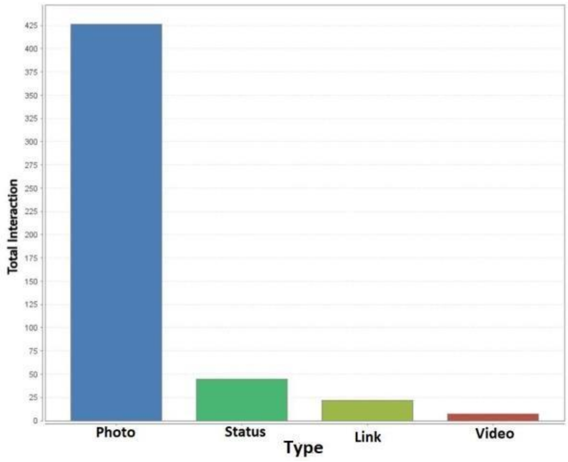

Figure 4: Impact of post type on total interactions

One crucial attribute i.e. page total likes also effected total interactions in a way that as page likes increases post interactions will also increase because more people will be viewing the post, but there are chances of getting negative comments as well because response from the unsatisfied customers will come up with adverse comments on the page **Figure 5** shows the effect.

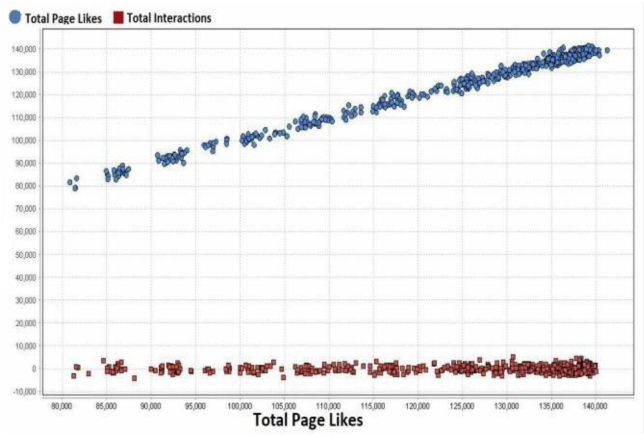

Figure 5: Relation between page likes and total interactions

In while Comparing post type and paid-unpaid attribute we can see that photos were posted without caring about paid or unpaid while status was most of the times paid. This also gives us an idea that photos can be posted without paying and it is already stated that photos get us most number of interactions by users.

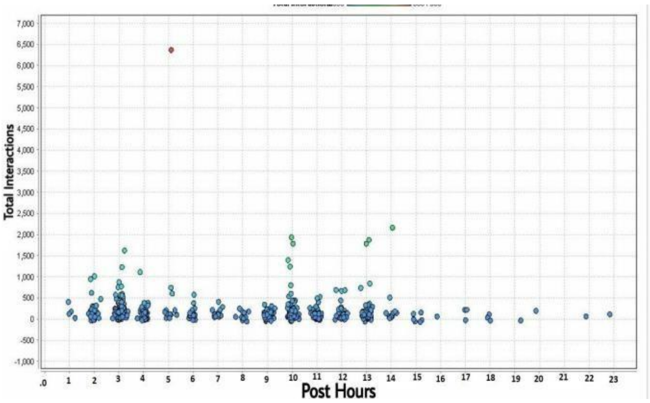

Figure 6: Impact of post hours on total interactions

Discussing post hour at which the users were most interactive, we can say that people were not so interactive during daytime and evening most of them were interactive at night and in the morning after midnight people were more interactive which can be seen as people were more emotionally active at night time. Moreover, less active during daytime.

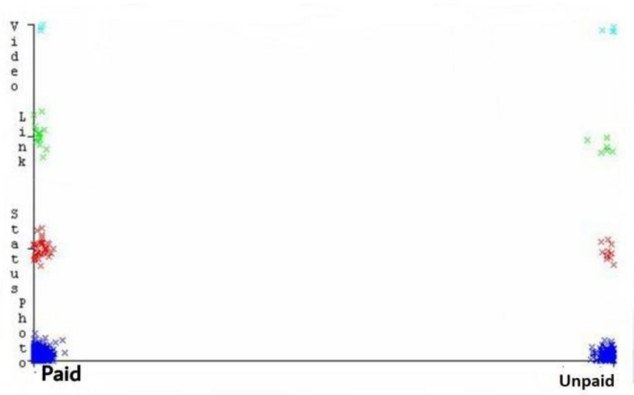

Figure 7: Distribution of paid and unpaid posts in the dataset

Figure 6 shows users' attitude during different posts time in detail. In **Figure 7** while Comparing post type and paid-unpaid attribute we can see that photos were posted without caring about paid or unpaid while status was most of the times paid. This also gives us an idea that photos can be posted without paying and it is already stated that photos get us the most significant number of interactions by users.

We also applied regression models to the data set. Results of linear regression revealed that the post's total interactions were most affected by category of the post (inspiration, product), Paid (yes, no), post month and post weekday which confirmed that targeting these input metrices can get us a number of interactions from customers. So, overall, we are presenting an idea that most of the interactions can be achieved on photos during the time ranging from 1 to 14 hours and on Friday and Saturday as people were more active in giving a response to the post on these days. We can claim that cognitively people were more intrigued by photos and during the start of year, i.e. Jan, Feb, March people were not so attracted to cosmetics. Page total likes effect people emotionally as they will be more curious about the products of the brand which has a large number of likes on their page.

V. CONCLUSION

The research focused on getting a maximum number of likes, comments, and shares from customers on social site Facebook which can help in brand building. We used a dataset of a cosmetic company with seven input metrices and 12 output metrices out of which we used total interactions which was calculated by adding likes, comments, and shares on a post. This study shows how advertising mangers can decide how to post about the product on social media to get maximum user interaction which will help in brand building. It revealed that photo from type, Saturday, Friday from weekdays and nighttime got us the most significant number of interactions. We conclude that posts should be targeting viewers cognitively and emotionally, i.e. through photos and specific time of day and week can lead to more interactions.

VI. ACCNOWLEGDEMENT

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