The Determinants of Social Media Engagement for Fashion Industry in Oman: A Descriptive Analysis

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Keywords: Digital Marketing, Customer Engagement, Instagram, Descriptive Analysis, K-means Cluster.

Abstract: The use of social media has completely remodelled the way people interact, communicate, and engage. Social media platforms play an essential role in reshaping the relationship between customers and companies. Present companies establish their accounts in social media to reach and engage with their customers, listen and take their opinion, enhance the purchase decision, and increase the revenue. The main goal of this study is to determine the factors that affect customer engagement. From 296 Instagram business accounts with 530,366 posts published, the dataset was scraped and used to understand what impacts customer engagement. Different descriptive analysis techniques were adopted to answer the questions of the study. Among the key finding of this study, customer engagement is positively affected by the number of comments and shares. The number of likes of published posts is not influenced. Moreover, video posts attract more customer interaction than other types of posts. Uncovered the property of three kinds of customer engagement (low, moderately, and high active).

1 INTRODUCTION

With the widespread of social media platforms, marketrs change their approach to communication with their current/potential customers. Social media marketing is considered an effective and fastest communication method to attract a large scale of customers to pay attention to the advertisement and pursue their purchasing decisions.

Social media is defined as a platform that permits individuals to design content, engage, or disseminate information, career interest, and pictures/videos through workable communication and networks (Sudarsanam, 2017). According to (Dolan et al., 2015), social media has empowered customers, flexibility, and visibility regarding marketing content that differentiates the interconnect between customer and organization. It transformed the customers from passive recipients of marketing content to active collaboration in the brand message.

Social media platforms such as Facebook, Twitter, YouTube, and Instagram provide a dialogue between companies and customers. Instagram, one of the social media platforms, allows users to publish text, images, and videos on their account page to interact with their followers /visitors. (Marketo, 2019) reported that 44% of active internet users use Instagram to research products. In Oman, 35% of the population can be reached by advertisements, as illustrated in Figure 1.

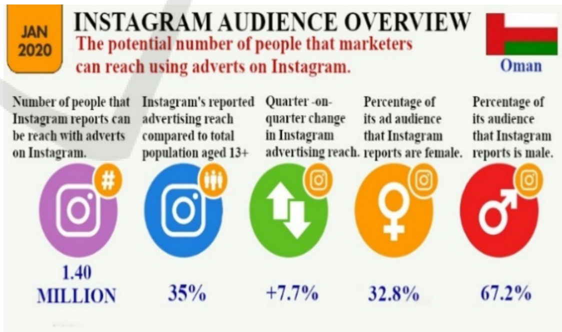

Figure 1: User of Instagram on Oman. https://datareportal.com/reports/digital-2020-oman.

Small businesses and retailers use Instagram as a tool to promote and sell their products and services. Using Instagram in marketing gives both the customers and advertisers the ability to communicate with each other. The customers can express their opinion about the advertising content or ask a question about it. The advertiser could answer the

Al Rabaani, F. and Said, A.
The Determinants of Social Media Engagement for Fashion Industry in Oman: A Descriptive Analysis.
DOI: 10.5220/0010336511511159
In *Proceedings of the 13th International Conference on Agents and Artificial Intelligence (ICAART 2021) - Volume 2*, pages 1151-1159
ISBN: 978-989-758-484-8

question and make an idea about how he could improve the advertising.

According to (Jordan, 2018), many small businesses and retailers need to understand how to deliver the advertisement to their customers. One of the most significant confrontations they faced is building an effective social media strategy to improve customer engagement on their social media web page. Most companies spend a lot of money on social media marketing campaigns. According to (Laudon & Traver, 2014), companies use online marketing campaigns, which require many efforts and cost a huge budget, to advertise and attract customers to their products and services without an increase in revenue.

The challenge is how to accomplish social media marketing's advantage to improve the relationship with customers and enhance revenue. Small businesses and retailers must spotlight a successful marketing campaign's characteristic to achieve a high level of customer engagement. Understanding the factors that affect customer engagement on social media leads to an increase in brand community engagement on social media. It will modulate the customer's attitudes toward the brand and increase company revenue.

According to (Shehu, 2018), with the massive posts published on social media platforms, businesses must collect, analyze, and act on customer data created on social media platforms. It provides an insight to attain competitive advantage and enclose brand relationships, product contentment, and service delivery. The aggregation of likes, comments, shares, and followers get actionable knowledge that small or medium companies can use to enhance their products and services and improve their content and delivery.

Data mining techniques supply a motivating approach for extracting knowledge from raw data. K-means clustering algorithm is one of the data mining models used to classify the data set to clusters based on the distance between the features of the data. It is an unsupervised machine learning technique that groups the data into subsets or clusters. Inside the same cluster, the data is very similar, while outside the cluster, the data is dissimilar. In this research, using K-means cluster to define the different groups of customer engagement in the fashion industry by utilizing the features of the data collection like:' type of posts published, number of likes, number of comments, number of shares, and other features' to identify the kind of customer interaction. Determining the different types of customer engagement helps the companies' decision-makers enhance engagement when delivering the marketing campaign on social media.

This research focused on how the Fashion Industry could use Instagram's business account to promote and market their products effectively. The objective of this research is to answer the following questions:

• Which type of posts attracts more interaction, and at what time of year, these posts get more interaction?

• Is there any difference in interaction on the posts type according to years?

• What are the most influential features of the customers' engagement?

• What are the prevailing characteristics of the existing social media accounts in the fashion industry?

The next section illustrates the overview of the literature review conducted in this area. The 3rd section describes the method used, the dataset, and selected features for the study. The 4th section answers the objective questions by explaining the results obtained after analyzing the study's dataset. The last section presents the main conclusions of this study.

2 LITERATURE REVIEW

Customer engagement on social media is one of the marketing objectives that enhance return on investment. Understand customer engagement and how it could measure it is one of the challenges that marketers seek to determine. Many kinds of literature were conducted to define customer engagement and provide a variety of concepts. Table 1 summarizes the definition of customer engagement in literature.

Motivating users to engage in social media platforms is an important challenge for researchers to gain insight into consumer engagement. (Khan, 2017) said comment behavior is a strong predictor to motive YouTube followers to engage with the video. When the follower writes a comment, that means he/she is interested in the content and adds a comment about what feels about the content. Like, dislike, comment, and upload reflect the motivation of engagement with the content published. The same result was founded by (BİLGİLİER, 2020). The researcher mentioned the importance of comments written on Instagram to improve the relationship between the customers and the company and increase customer engagement. The type of post published has a significant impact on lifetime post consumers.

Table 1: Customer engagement related concept.

Author	Concept	Definition
Perreault & Mosconi (2018)	Brand and consumers' engagement	Customers engage in several behaviors that strengthen their relationship with the brand, which go beyond the traditional customer loyalty measures such as, frequency of visits, purchasing behavior, and intended actions [such as, sharing, commenting, and liking the brand page].
Volkmann et al.(2019)	User-generated content	Many consumers voluntarily publish on the internet and express their experiences, opinions, feelings, and perceptions online on the social network, in fora, blogs, or product review channels.
Kuntara et al.(2019)	User engagement in social commerce	Factors affecting user participation include trust, information quality, attitude, community involvement, perceived usefulness, and social support.
Oliveira & Goussevskaia (2020)	User engagement	The function of the number of interactions (likes and comments) with the post, and the number of followers of the poster
Vadivu & Neelamalar (2015)	Customer engagement	Sequential psychological process in which customers move through to become loyal towards a brand. In online customer engagement in social media platforms, it is characterized by customer interactivity with the brand.

This result was founded by (Huey & Yazdanifard, 2015) and (Janani & Prabhalammbeka, 2017). They found "Status" posts get the highest number of comments, "video" posts get the most likes, and "Photos" and "links" get the lowest number of interactions on customer engagement. Besides, they found the seasonality "month of published posts" has a significant impact on user engagement with the posts published. The type of content published, "persuasive, or informative," has a substantial impact on customer engagement "like and comment". (Lee et al., 2018) said that persuasive content has a positive effect on customer engagement while informative content reduces the engagement.

Several previous researchers have done the metrics that used to calculate and evaluate the engagement on social media. The formula used to measure the engagement varies between the researches, but all the researchers adopted the number of comments, likes, posts, and followers as the most important metrics. (Vrana et al., 2019) adopted number of followers, number of following, and number of likes as metrics to determine customers' engagement. The more followers an account has, the more impact the account has. (Barnes & Rutter, 2019; Muhammad et al., 2018; Segev et al., 2018) also used the same metrics in their researches. (Yew et al., 2018) suggested a new measurement to evaluate the engagement. They used the average number of likes, the average number of comments, and the average number of views for the video posts and out of the total number of posts in the last three months divided by the average of reach achieved in the last three months. (Arman & Sidik, 2019) suggest new formula to calculate the engagement because they viewed that number of comments, likes, and followers as crucial metrics to determine the engagement and the number of posts in the page account and the probability for followers to see the posts. They considered that not all the likes and comments that post has come from the business page's followers. It also may become from the visitors of the business page. (Mariani et al., 2017) add the number of shares in their formula to calculate the engagement. They calculate the number of likes, comments, and shares for the post and divided by total posts, then multiplied by 100 to get the engagement rate. They consider that most of the business page's followers or visitors could click like to the post, some of them write a comment, and who is interested in the post will share it with others.

Some studies focused on customer engagement and used different data mining techniques and algorithms to understand what motivates them to engage in social media. (Segev et al., 2018) using regression models (Ridge Regression and Random Forest), they found that Multi-Regression was not a beneficial method while feature reduction resulted in powerful models. (Oliveira & Goussevskaia, 2020) adopted a classification model (Extremely Randomized Tree algorithm) to classify the features that affect customer engagement on Instagram, also used (Area Under the ROC Curve 'AUC') to evaluate the model. They found that the average text size is the most notable feature. (Arman & Sidik, 2019) referred that used data mining approach, but the authors don't describe any algorithm that adopted. They used correlation analysis and arithmetic mean to analyze the engagement. (Lee et al., 2018) build NLP algorithm to understand customer engagement on FaceBook and adopted (accuracy, recall, precision) to evaluate the algorithm. This algorithm achieves 99% accuracy. Besides, adopting a descriptive analysis.

(Muhammad et al., 2018) implemented a K-means algorithm to classify the posts published on Instagram and used five variables (day, hours, likes, comments, and location name). The result indicated that the data set was classified into three different clusters. Also, they used descriptive analysis to visualize customer engagement. (Barnes & Rutter, 2020) discussed some big data and artificial intelligence techniques (V3 convolutional neural network) to describe customer engagement on social media Influencer posts. They found that general influencer gains the best performance while traveling influencers accomplished greater overall engagement and implementing some data visualization.

According to (Anitha & Patil, 2019), k-means clustering is a data mining technique applied to discover the different customer predilection patterns in the fashion industry. (Ližbetinová et al., 2019) Understanding the data set feature by adopting descriptive analysis is essential before applying the clustering. Clustering is a technique to different entities into a subset of groups. The entities inside the same group or cluster share the same properties. K-means algorithm is a popular classification algorithm (Gurusamy et al., 2017).

3 METHODOLOGY

This research investigates and analyses the Instagram account page of small businesses and retails from Oman's fashion industry.

3.1 Dataset Collection

To identify the main Omani fashion industry business account on Instagram, WhatsApp Groups was created to ask regular purchasers from online customers to suggest three different accounts from the fashion industry that follow and purchase from them. These accounts must be Omani ones. In addition to that, the researchers relied on suggestions of accounts done by the Instagram platform. As a result of identifying the fashion industry accounts, 305 were selected. After checking all the accounts' status, the researchers decided to reject some of the accounts because they were inactive, making the final number of accounts 296. The total number of the collected posts was 530,366 from all the 296 Instagram business accounts published in a period above seven years from 11/12/2012 until 10/7/2020.

3.2 Dataset Features

The data set's input features have been collected from both the business account profile and the posts published in the account. It is categorized into two types directly taken from the business account page or computed from other features. Table 2. explains all the selected features used for this research with its description.

3.3 Calculation of Customer Engagement

The measure used to evaluate customer engagement was adopted from (Mariani et al., 2017). The reason for using this formula is because not all the likes, comments, shares that the post gets come from the follower of the business account. It may become from any visitor to the account, as mentioned in (Mariani et al., 2017) and (Arora et al., 2019). Equation 1 illustrates the adopted formula in this study.

$$ER_{\mathcal{P}} = \frac{\mathcal{L}+\mathcal{C}+\mathcal{S}}{\mathcal{P}} \times 100 \quad (1)$$

Where "$\mathscr{L}$" denotes the number of likes post, "$\mathcal{C}$" indicates the number of comments, "$\mathcal{S}$" indicates the number of shares, "$\mathcal{P}$" indicates the number of total posts in the account, and "ER$\mathcal{P}$" denotes Engagement Rate for each post.

The study is a descriptive analysis. To answer research questions, the researchers are going to use statistical measurement and different visualization techniques. In addition, the data analysis in this research is adopting K-means to define the prevailing characteristics of the existing social media accounts.

4 ANALYSIS AND RESULTS

To acquire a general understanding of how Instagram, brand page accounts are applied to enhance marketing engagement customers, first investigate the descriptive statistic for the selected factor variables of profile feature account. Table 3 provides the descriptive statistic value for the features.

Regarding the posts published type, graph Image is most frequently (401731 occurrences, 75.75% of total), followed by graph side care (96337 occurrences, 18.16%), graph video has the lowest frequency (32298 occurrences, 6.09% of total). In aggregated posts published over the seven years, more than 50000 posts were published in (May, June, March), and less than 40000 posts were published in (August, September). The result indicates the trade of fashion industry in Oman is booming in May due to upcoming the season of end of the school year, and Summer holidays, besides, the trade of fashion industry decreases in August and September as the interest of consumers shifts to prepare for the start of the School year. Figure 2. shows the aggregation of posts published over the seven years in the month.

280160 posts from all the posts published did not have any comments or shares. When focusing more on these posts, why didn't the posts get any comments or shares? Finding 12443 posts on the account page, Instagram users disabled the followers or visitors to add a comment for these posts, while 267717 did not interest the followers or visitors to add comments or share it, even if these posts get several likes.

Table 2: Dataset features.

Feature	Type of feature	Description
Follower count	Directly taken	Number of followers who follow the page of the business account.
Following count	Directly taken	Number of following that the user of account following them.
Posts count	Directly taken	Total number of posts published that in the business account page.
Post type	Directly taken	Type of post published (three types of posts published Graph Image, Graph Side care, and Graph Video)
Video view count	Directly taken	Total number of views that the video post got.
No of likes	Directly taken	Total number of likes that the post got.
No of comments	Directly taken	Total number of comments that post gain it.
No of shares	Computed	Total number of shares that the post gain it.
Comment disabled	Directly taken	The boolean type determines of the user disabled the Comment for the followers who saw the post or not.
Last comment date	Computed	Date Time type, last date that the posts got Comment.
Time publishing	Directly taken	At the time that the post published
day	Computed	Day of the post published (get from Time publishing)
month	Computed	The month the post published (get from Time publishing)
year	Computed	The year of post published (get from Time publishing)
Ave_ like	Computed	The average number of all number of likes that the account got from all posts in the account.
Ave_ comment	Computed	Average number of all the number of comments that the account got from all posts in the account.
Ave_ Share	Computed	Average number of all number of shares that the account got from all posts in the account.
Is a business account	Directly taken	Determine if the user of the account makes his/her account business account or not. This feature provided by Instagram for any account can use this feature and then get analysis details for the account.
Is private	Directly taken	Some user makes their profile private, then allowed for who want to follow them or not.

Table 3: Statistic value of profile feature account.

	Posts count	Video view count	No of likes	No of share	No of Comment	Ave_ video view	Ave_ like	Ave_ share	Ave_ comments	Followers count	ER
Count	530,366	322,98	530,366	530,366	530,366	270	296	296	296	296	530,366
Mean	15,140	1,985	62	3	6	2,84	101	15	27	52,62	8
Std	20,090	6,384	324	285	377	11,41	226	175	284	67,56	1,12
Min	18	0	0	0	0	0	1	0	0	175	0
25%	2,123	143	5	0	0	451	17	0	2	10,63	0
50%	6,769	549	13	0	0	1,17	40	1	4	29,68	0
75%	16,009	1,747	38	1	3	2,24	102	3	11	716,9	2
Max	633,02	334,404	30,792	147,07	237,92	169,65	2,96	3,01	4,88	734,53	816,01

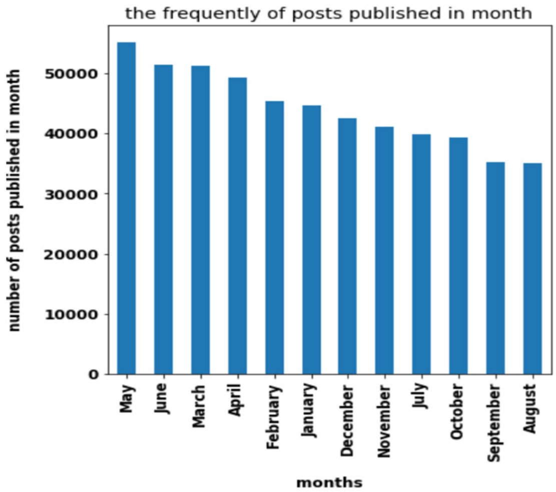

Figure 2: Aggregation of posts published over the 7 years in the month.

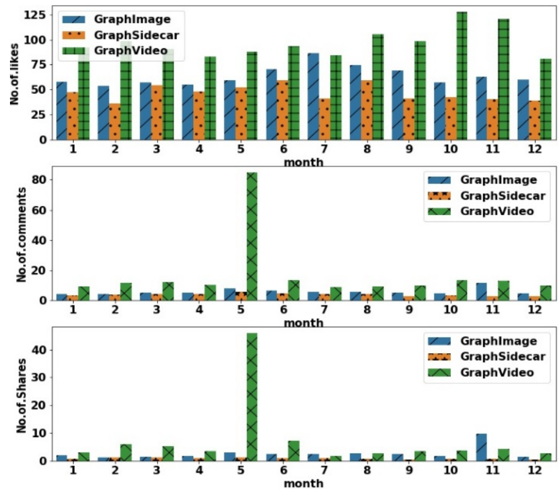

Figure 3: The different of the interaction posts type in month.

The Comments and Shares take time for the followers to add, and if the post attracts the follower's interest, the follower will add a comment. The result supports the previous literature in important comments to make relationships with customers and improve the interaction between the customers and the company (Vadivu & Neelamalar, 2015).

• Which type of posts attracts more interaction, and at what time of year, these posts get more interaction?

The posts type "Graph Video" receives the highest average rate of likes, comments, and shares overall the months in the year except in November, the post type "Graph Image" gets the highest average rate of shares. "Graph Video" gets the highest average rate of likes in October and November this is because upcoming of the season end of year discounts and the National Day, while "Graph Image" gets the highest average rate of likes in July and August, and "Graph Sidecar" gets the highest average rate of likes in June and August. "Graph Video" receives the highest average rate of comments and shares in May, while "Graph Image" gets the highest average rate of comments and shares in November, and "Graph Sidecar" gets the highest average rate of comments and shares in May. Posts type "Graph Video" has the best interaction. Figure 3. illustrates the difference between the interaction type of posts in the month.

• Is there any difference in interaction on the posts type according to years?

The posts type "Graph Sidecar" starts appearing in 2017 and has average increase interaction (likes, comments, and shares) over the years. "Graph Image" has an oscillatory performance of interaction over the years. "Graph video" gets the highest average rate of likes in 2015 while getting the highest average rate of comments and shares in 2020. Figure 4. illustrates the difference between the interaction types of posts in years.

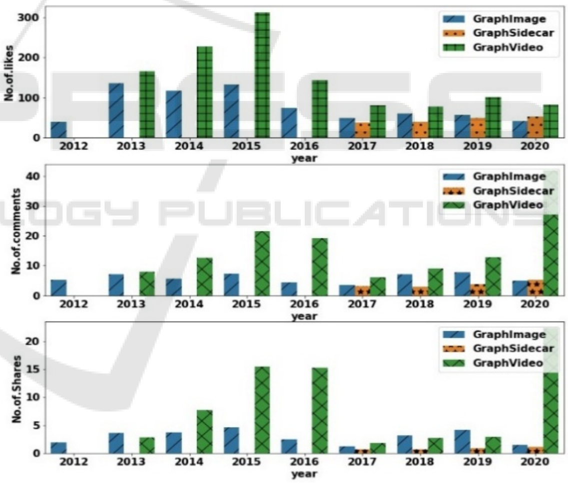

Figure 4: The different of the interaction posts type in year.

• What are the most influential features on the customers' engagement?

Table 4. demonstrates the correlation coefficient between the Features for every post published, there is a significant positive correlation between the engagement rate and the No of Comments and No of Shares, 0.879, 0.726, respectively. This result means that the marketer must focus to the comments and shares to understand what the customers need and interest. The relationship between number of comments and number of shares is very high positively, 0.929 the comments and shares very

related to each other. This means if the follower or visitor writes a comment for the post published the probability to share this post with others is very high. No relationship between Posts Count and No of Likes, No of Comments, No of Shares, and Engagement Rate. The result suggests that it is not important to publish more posts to get follower's and visitor's interaction.

Table 4: The correlation coefficient between the Features for every post published.

	posts count	No of likes	No of Comment	No of Share	E R
posts count	1.000	-0.099	-0.009	-0.006	-0.01
No of likes	-0.099	1.000	0.121	0.105	0.09
No of comment	-0.009	0.121	1.000	0.929	0.88
No of Share	-0.006	0.105	0.929	1.000	0.73
Engagement Rate	-0.005	0.085	0.879	0.726	1.00

Figure 5. shows the correlation between the features of average business accounts, there is a significant positive corelation between Total posts and Total video posts, 0.67. The Average video view affects high positively the Average Likes, Comments and Engagement Rate (0.90) and medium positively to the average likes (0.42). Followers count affects high positively to the average likes (0.62). The Average likes have low positively affected the Average Comments, Engagement Rate, and Shares, 0.22, 0.23, 0.19, respectively. Average Comment has a very high positive relationship with the Average Engagement Rate and Shares, 0.99, 1, respectively. Average Shares has a very high positive relationship with the Average Engagement Rate, 0.98.

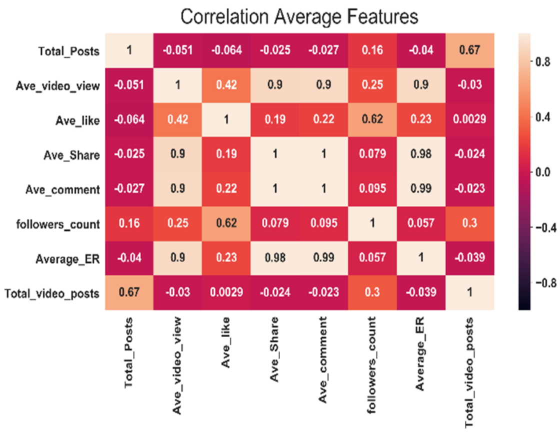

Figure 5: The correlation between features of average business accounts.

• What are the prevailing characteristics of the existing social media accounts in the fashion industry?

The Elbow curve method helps estimate the number of prevailing characteristics of the existing social media accounts in the fashion industry. It is used to determine the maximum and a minimum number of clusters in the dataset. This method applied several K-mean clusters by increasing the number of K (number of clusters in the dataset) every iteration and recorded the sum of square error (SSE). The goodness of cluster function is estimated by computing the SSE after the centroids coverage. The SSE is realized as the sum of squared Euclidean of each point to its adjacent centroid. The lowest value of SSE is the best for the number of clusters. As a result, there are two to four different clusters in the dataset, as figure 6 shows.

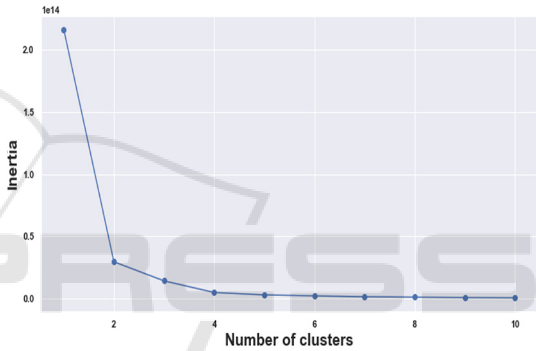

Figure 6: Maximum and minimum number of clusters.

Based on clustering analysis adopting K-means Algorithm (Muhammad et al., 2018), posts published in business account in Oman's fashion industry are divided into three groups. The first cluster has 527921 posts. The second cluster has 62 posts, while in the third cluster there are 2380 posts. Table 5. describes the most important features that describe and categorize the interaction that posts get (Posts type, Video view count, No of likes, No of shares, No of comments, day, month, year, and Engagement rate). For instance, Clusters # 1 shows posts with low interaction the midpoints of features (posts type of Graph Image, 55.3 Video view count, 59.6 Likes, 2.2 Shares, 5.3 Comments, the day of Wednesday in June 2017, and 6.1 Engagement Rate). Cluster # 2 shows posts with high interaction; the midpoints of features are (posts type Graph Video, 108880.9 Video view count, 6087.3 likes, 26.9 Shares, 207.3 Comments, the day of Thursday in May 2018, and 466.9 Engagement Rate). Cluster#3 shows posts with moderate interaction; the midpoints of features are (posts type of Graph Video, 11769.6 Video view

Table 5: The K-means Features midpoints clusters.

	Posts type	Video view count	No of likes	No of shares	No of comments	day	month	Year	E_R	Interaction type
Cluster0	0.295587	55.32	59.61	2.25	5.37	2.96	6.23	2017.99	6.12	low interaction
cluster1	2	108880.92	6087.32	26.90	207.32	3.65	5.92	2018.76	466.98	high interaction
cluster2	2	11769.66	456.49	24.00	70.61	2.98	5.91	2018.86	60.97	moderate interaction

count 456.5 likes, 23.9 Shares, 70.6 Comments, the day of Wednesday, in May 2018, and 60.9 Engagement Rate). Table 5 shows the clusters' Feature midpoints.

5 CONCLUSION

The current research aims to analyze and investigate Instagram's customer engagement in the fashion industry and who could use Instagram as a marketing tool. 296 Instagram users account with 530366 posts published on their Instagram page account was used in this research. The analysis comes with the significant result that:

- comments and shares are critical factors that affect the customer's engagement on Instagram fashion industry accounts.
- The interest in publishing more posts does not lead to attract more customer engagement.
- Most of the posts published get low-performance interaction. This result shows that the users of business account pay more attention to publishing posts than listening to what people say about their products.
- The post type "Graph Video" attracts more interaction than the other types of posts.
- When marketers want to establish a marketing campaign on Instagram, they should adopt the type post "Graph Video" to receive more followers and visitors' interaction.
- When the fashion industry marketers want to establish a marketing campaign and attract more interactions and opinions about the products from the followers or attract new followers to their account, the best month to develop this campaign in May, October, or November.

REFERENCES

Anitha, P., & Patil, M. M. (2019). RFM model for customer purchase behavior using K-Means algorithm. Journal of King Saud University - Computer and Information Sciences, 1–8. https://doi.org/10.1016/j.jksuci.2019.12.011

Arman, A. A., & Sidik, A. P. (2019). Measurement of Engagement Rate in Instagram (Case Study: Instagram Indonesian Government Ministry and Institutions). 2019 International Conference on ICT for Smart Society (ICISS). doi:10.1109/iciss48059.2019.8969826

Arora, A., Bansal, S., Kandpal, C., Aswani, R., & Dwivedi, Y. (2019). Measuring social media influencer index-insights from facebook, Twitter and Instagram. Journal of Retailing and Consumer Services, 49, 86-101. doi:10.1016/j.jretconser.2019.03.012

Barnes, S., & Rutter, R. (2019). Using Big Data and AI to Examine Product Engagement in Social Media Influencer Posts. 2019 4th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE). doi:10.1109/icitisee48480.2019.9003991

BİLGİLİER, H. S. (2020, January 29). (PDF) Instagram in the Context of Dialogic Communication ... Retrieved February 24, 2020, from https://www.researchgate.net/publication/341741528_Instagram_in_the_Context_of_Dialogic_Communication_A_Content_Analysis_for_Top_Performing_Brands_on_Instagram.

Dolan, R., Conduit, J., Fahy, J. and Goodman, S., 2015. Social media engagement behaviour: a uses and gratifications perspective. Journal of Strategic Marketing, 24(3-4), pp.261-277.

Gurusamy, V., Kannan, S., & Prabhu, J. R. (2017). Mining the Attitude of Social Network Users using K-means Clustering. International Journal of Advanced Research in Computer Science and Software Engineering, 7(5), 226-230. doi:10.23956/ijarcsse/sv7i5/0231

Huey, L. S., & Yazdanifard, D. (2015). How Instagram Can Be Used as a Tool in Social Network Marketing. Social Networking Marketing. Retrieved from https://www.researchgate.net/publication/265377226.

Janani, P., & Prabhalammbeka, B S. (2017). PREDICTING THE INFLUENCES OF SOCIAL NETWORKS ON BRAND BUILDING. International Journal of Mechanical Engineering and Technology, 8(10), 0976-6359, 308-317. Retrieved October, 2017.

Jordan, R. S. (2018). Social Media Marketing Strategies Used by Small Retail Businesses (Master's thesis, Walden University, October 2018) (pp. I-110). East Eisenhower Parkway: ProQuest LLC.

Khan, M. L. (2017). Social media engagement: What motivates user participation and consumption on

YouTube? Computers in Human Behavior, 66, 236-247. doi:10.1016/j.chb.2016.09.024
Kuntara, I., Purwandari, B., Purwaningsih, M., & Kumaralalita, L. (2019). Factors Influencing Consumer Engagement on Instagram: A Perspective of Bereal.id. 2019 Fourth International Conference on Informatics and Computing (ICIC). doi:10.1109/icic47613.2019.8985730
Laudon, K. C., & Traver, C. G. (2014). E-commerce: Business, technology, society (Tenth Edition ed.). Harlow, England: Pearson.
Lee, D., Hosanagar, K., & Nair, H. (2018). Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook. SSRN Electronic Journal. doi:10.2139/ssrn.2290802.
Ližbetinová, L., Štarchoň, P., Lorincová, S., Weberová, D., & Průša, P. (2019). Application of Cluster Analysis in Marketing Communications in Small and Medium-Sized Enterprises: An Empirical Study in the Slovak Republic. Sustainability, 11(8), 2302. https://doi.org/10.3390/su11082302.
Mariani, M. M., Mura, M., & Di Felice, M. (2017). The determinants of Facebook social engagement for national tourism organizations' Facebook pages: A quantitative approach. Journal of Destination Marketing & Management, 8, 312–325. https://doi.org/10.1016/j.jdmm.2017.06.003
Marketo. (2019). The definitive guide to social media marketing (pp. 1-83, Publication). Adobe.
Muhammad, H., Wahiduddin, F., Budi, N. F., & Hidayanto, A. N. (2018). An Integrated Framework to Investigate Influencing Factors of Users Engagements on Instagram Contents. 2018 Third International Conference on Informatics and Computing (ICIC). doi:10.1109/iac.2018.8780511
Oliveira, L. M., & Goussevskaia, O. (2020). Sponsored content and user engagement dynamics on Instagram. Proceedings of the 35th Annual ACM Symposium on Applied Computing. doi:10.1145/3341105.3373956
Perreault, M., & Mosconi, E. (2018). Social Media Engagement: Content Strategy and Metrics Research Opportunities. Proceedings of the 51st Hawaii International Conference on System Sciences, 3668-3577. doi:10.24251/hicss.2018.451
Segev, N., Avigdor, N., & Avigdor, E. (2018). Measuring Influence on Instagram. The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, 1009-1012. doi:10.1145/3209978.3210134
Shehu, M. (2018). Formalizing social media marketing strategies. Proceedings of the Second African Conference for Human Computer Interaction on Thriving Communities - AfriCHI 18, 145-149. doi:10.1145/3283458.3283485
Sudarsanam, S. K. (2017). Social Media Metrics. Social Media Listening and Monitoring for Business Applications Advances in E-Business Research, 131-149. doi:10.4018/978-1-5225-0846-5.ch007
Vadivu, V. M., & Neelamalar, M. (2015). Digital brand management — A study on the factors affecting customers engagement in Facebook pages. 2015 International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM). doi:10.1109/icstm.2015.7225392
Volkmann, G., Egger, M., & Schoder, D. (8-14/6/2019). TOWARDS MINING BRAND ASSOCIATIONS FROM USER-GENERATED CONTENT (UGC): EVIDENCE FROM LINGUISTIC CHARACTERISTICS. European Conference on Information Systems. Retrieved from https://aisel.aisnet.org/ecis2019_rp/82.
Vrana, V. G., Kydros, D. A., Kehris, E. C., Theocharidis, A. T., & Kavavasilis, G. I. (2019). Top Museums on Instagram. International Journal of Computational Methods in Heritage Science, 3(2), 18-42. doi:10.4018/ijcmhs.2019070102
Yew, R. L., Suhaidi, S. B., Seewoochurn, P., & Sevamalai, V. K. (2018). Social Network Influencers' Engagement Rate Algorithm Using Instagram Data. 2018 Fourth International Conference on Advances in Computing, Communication & Automation (ICACCA). doi:10.1109/icaccaf.2018.8776755.