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Research Paper

The Importance of Social Media Marketing

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ABSTRACT
In the 21th Century, the importance of social media in marketing is increasing day by day. Now a day, it become important to target the audience via a social networking mode. In order to attract the public, the cheapest mode is through this. In this research paper, different variables are taken in order to target audience through social media mode that is Facebook. The factor analysis tool has taken to analysis this model.

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I. INTRODUCTION

With the help of social media channel, the market can target the right audience at right time. In order to satisfy the customer, certain mechanism had utilized to figure out the calculation. Let take a several questions all driving at different, but closely related, aspects of customer satisfaction:
Q1: How many people likes your post on Social Media.
Q2: Lifetime Post Total Impressions on them?
Q3: Lifetime Post Impressions by people who have liked your Page?
Need to take one variable that will represent a customer satisfaction score. One option would be to average the three question responses. Another mode is to take use of factor dependent variable (PCA Model). The advantage of PCA over an average is that it automatically weights each of the variables in the calculation.

Conducting Factor Analysis

- Is data suitable for analysis?
- How factor are extracted?
- What are the criteria to determine?
- Selection of the method of rotation?
- Interpretation and Labeling?

The basic assumption of factor analysis is that for a collection of observed variables there are a set of underlying variables called factors (smaller than the observed variables), that can explain the interrelationships among those variables.

II. METHODOLOGY

The techniques used in this paper:
Interdependence Technique and Scale Development. Let’s conduct a survey and collect responses about “total post likes” in order to collect market research about the usage of social networking site.
Let’s proceed with the survey which terms the Total Post with the help of the Questionnaire. This consists of the following questions:

1. Page total likes
2. Lifetime Post Total Reach
3. Lifetime Post Total Impressions
4. Lifetime Engaged Users
5. Lifetime Post Impressions by people who have liked your Page
6. Lifetime Post reach by people who like your Page

7. Total Interactions

In order to test the suitability of the factor analysis, we need to apply Standard Rule of Thumb. It states that number of factor respondents should be more than 5n (n: variables/ constructs). In our case we have 7 constructs so; the number of responses should be more than 35.

Kaiser- Meyer- Olkin (KMO)

This Test Checks the adequacy of data for running the factor analysis. The value of KMO ranges from 0 to 1. The larger the value of KMO more adequate is the sample for running the factor analysis. Kiaser recommends accepting values greater than 0.5 as acceptable.

Bartlett test of significance

It test the null hypothesis that all the correlation between the variables is zero. It also whether the correlation matrix is a identity matrix or not. If it is an identity matrix then factor analysis becomes in appropriate.

Table 1: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.678
Bartlett's Test of Sphericity	Approx. Chi-Square	5524.779
	df	28
	Sig.	0

Table 1 represents the KMO measure is 0. 678 therefore can be accepted. From the same table, we can see that the Bartlett's Test of Sphericity is significant (0.00). That is, significance is less than 0.05. This means that correlation matrix is not an identity matrix. In order to analysis the **pattern of correlation** between variables, factor analysis will be used. It helps correlate the variables. If variables are highly correlated, likely that they represent the same underlying dimension. Factor Analysis pinpoints the **cluster of high correlations** between variables and for each cluster, **it will assign a factor**.

With respect to Correlation Matrix if any pair of variables has a value **greater than 0.3 and above then it's a reasonable explanatory variable**. If there are sufficient of such coefficients, the **Factor analysis is applicable**.

Table 2: Correlation Matrix

Correlation Matrix								
The correlation matrix	Page total likes	Lifetime Post Total Reach	Lifetime Post Total Impressions	Lifetime Engaged Users	Lifetime Post Impressions by people who have liked your Page	Lifetime Post reach by people who like your Page	like	Total Interactions
Page total likes	1	-0.082	-0.102	-0.111	-0.096	-0.059	0.053	0.046
Lifetime Post Total Reach	-0.082	1	0.695	0.57	0.322	0.743	0.545	0.538
Lifetime Post Total Impressions	-0.102	0.695	1	0.368	0.851	0.652	0.345	0.343
Lifetime Engaged Users	-0.111	0.57	0.368	1	0.26	0.612	0.57	0.572
Lifetime Post Impressions by people who have liked your Page	-0.096	0.322	0.851	0.26	1	0.584	0.253	0.25
Lifetime Post reach by people who like your Page	-0.059	0.743	0.652	0.612	0.584	1	0.632	0.618
like	0.053	0.545	0.345	0.57	0.253	0.632	1	0.998
Total Interactions	0.046	0.538	0.343	0.572	0.25	0.618	0.998	1

III. METHOD OF FACTOR ANALYSIS

Principal component Analysis

Statistical techniques used for data reduction or structure detection, Variables that are correlated with one another but are largely independent of other sets of variables are combined into factors. The factor explaining the maximum variance is extracted first.

Table 3: Communalities

Communalities		
	Initial	Extraction
Page total likes	1	0.14
Lifetime Post Total Reach	1	0.676
Lifetime Post Total Impressions	1	0.905
Lifetime Engaged Users	1	0.574
Lifetime Post Impressions by people who have liked your Page	1	0.792
Lifetime Post reach by people who like your Page	1	0.805
like	1	0.906
Total Interactions	1	0.901
Extraction Method: Principal Component Analysis.		

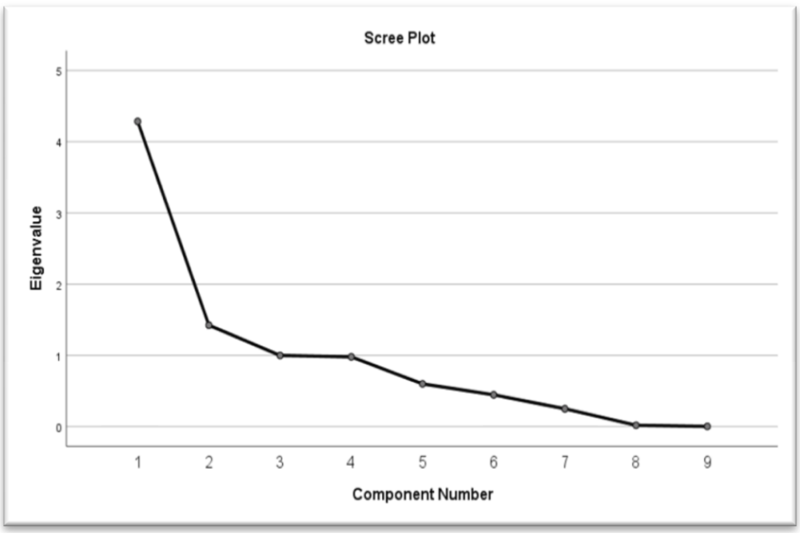
How factor are extracted?
Communalities
The next item from the output is a table of communalities which shows **how much of the variance** (i.e. the community value which should be **more than 0.5 to be considered for further analysis.** Else these variables are to be removed from further steps factor analysis) in the variables has been accounted for by the extracted factors.

Total variance explained
Eigenvalues represent the total amount of variance that can be explained by a given principal component. If eigenvalues are greater than zero, then it's a good sign.
If there is a low eigen value of a factor, then its contribution to the elaboration of variances in variables is less and might not be taken as redundant with other significant factors. The Eigen value table has been divided into three sub-sections, i.e. Initial Eigen Values, Extracted Sums of Squared Loadings and Rotation of Sums of Squared Loadings. For analysis and interpretation purpose we are only concerned with Extracted Sums of Squared Loadings. **Here one should note that Notice that the first factor accounts for 53.469 % of the variance and the second 17.767 %. All the remaining factors are not significant.**

Table 4: Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadingsa
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4.277	53.469	53.469	4.277	53.469	53.469	3.906
2	1.421	17.767	71.236	1.421	17.767	71.236	2.287
3	0.986	12.324	83.56				
4	0.6	7.504	91.064				
5	0.446	5.571	96.634				
6	0.25	3.119	99.753				
8	0.002	0.025	100				

The Scree plot



The scree plot is a graph of the eigen values against all the factors. The graph is useful for determining **how many factors to retain.** The point of interest is where the curve starts to flatten. It can be seen that **the curve begins to flatten between factors 3 and 4.** Note also that factor 4 onwards have an eigenvalue of less than 1, so only three factors have been retained.

Component matrix

Contains the factor loadings, which are the correlations between the variable and the factor. The **higher the absolute value of the loading, the more the factor contributes to the variable** (we have extracted 3 variables wherein the ***8 items are divided into 3 variables)*** The **gap** (empty spaces) on the table represent loadings that are **less than 0.5**, this makes reading the table easier. We **suppressed** all loadings less than 0.5.

Table 5: Component Matrix

Component Matrix	Component	
Lifetime Post reach by people who like your Page	0.893	
Lifetime Post Total Reach	0.821	
like	0.807	0.505
Total Interactions	0.802	0.507
Lifetime Post Total Impressions	0.766	-0.564
Lifetime Engaged Users	0.728	
Lifetime Post Impressions by people who have liked your Page	0.622	-0.636
Page total likes		0.366
Extraction Method: Principal Component Analysis.		

Pattern Matrix and Structure matrix

Table 6: Pattern Matrix

Pattern Matrix		
	Component	
	1	2
like	0.974	
Total Interactions	0.971	
Lifetime Engaged Users	0.74	
Lifetime Post reach by people who like your Page	0.717	-0.407
Lifetime Post Total Reach	0.675	-0.347
Lifetime Post Impressions by people who have liked your Page		-0.837
Lifetime Post Total Impressions	0.337	-0.821
Page total likes		0.378

Table 7: Structure Matrix

Structure Matrix		
	Component	
	1	2
like	0.935	
Total Interactions	0.931	
Lifetime Post reach by people who like your Page	0.804	-0.56
Lifetime Engaged Users	0.755	
Lifetime Post Total Reach	0.749	-0.49
Lifetime Post Total Impressions	0.512	-0.893
Lifetime Post Impressions by people who have liked your Page	0.351	-0.873
Page total likes		0.349

Pattern matrix appears to be the main tool for interpretation. Coefficients of pattern matrix are the unique loads or investments of the given factor into variables. Because it is regression coefficients. **The variable with the strongest association to the underlying latent variable. Factor 1, is income, with a factor loading of 0.97. Since factor loadings can be interpreted like** standardized regression coefficients**, one could also say that the variable "like" has a correlation of 0.97 with Factor 1. Structure matrix** contains (zero-order) correlations between factors and variables. The more two factors X and Y correlate with each other the greater can be the discrepancy between the pattern loadings and the structure loadings on some variable V. While V ought to correlate higher and higher with both factors, the regression coefficients can rise both or only one of the two. The latter case will mean that it is that part of X which is different from Y what loads V so much; and thence the V-X pattern coefficient is what is highly valuable in interpretation of X.

IV. CONCLUSION

Factor analysis helped to find out and cluster the variables. This model explained the Statistical techniques used for data reduction or structure detection.

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