ISSN 2319 – 1953
International Journal of Scientific Research in Computer Science Applications and Management Studies

The Positive Impact of Social Networking Sites on the Consumer Buying Behavior of Youth in Theni District

K. Rani[#1], M. Dharani[* 2], J. Jerina[@3]
[#1] *Assistant Professor, Department of Computer Science,*
Jayaraj Annapackiam College for Women (Autonomous), Periyakulam. Theni(Dt),Tamil Nadu
[*2,@3] *PG Students, Jayaraj Annapackiam College for Women (Autonomous), Periyakula,. Theni(Dt),Tamil Nadu*
[1]ranijosmsc@gmail.com, [2]dharu97bsc@gmail.com, [3]Jerinajabar1996@gmail.com

***Abstract*- Social media sites have given plenty of opportunities to consumers in adapting different aspects in life. This can be linked to a positive association providing active value that assists Youth in making decisions about what product to buy, when to buy, and where to buy. Facebook, Twitter, Snapchat, Instagram and Whatsapp have played significant roles in expanding youths' online purchases. The corporate have to develop new marketing mode to reach their youth to purchase through social networking sites. Especially seeing the loving curiosity in the purchase intensity by young people, marketers add the social media applications to their marketing strategies. Young people who follow attention envelopments, technological developments and fashion are young consumers. Also young people are the consumers who are the most interested in mobile technologies too to purchase the item. The benefit of E-Marketing is the contribution to reducing environmental pollution and prevention of degradation. For that reason, this study is to identify the effect of the mobile social networking sites on young consumers' spending expenditure. The questionnaire was administered to different College Students of Theni District. The results were analyzed with R tool.**

***Keywords*- Social media networking, consumer's behavior, social media market, Young Consumers, Purchase Intention.**

I. INTRODUCTION

Word of mouth has always been an effective marketing tool for business. In 2013, that word of opening is just as likely to come from a social media website or Smartphone application as from a neighbor across the enclosure. According to character modifier, a community management consulting company, 90 percent of Smartphone users turn to their mobile to shopping and most of them look for suggestions and references from a number of sources to help them make their buying decisions. One of the reasons that the Internet in general and social media in particular are so effective for consumers is that it's fast. Corporate can easily look up the consumers hours of operation, address and online shopping opportunities while they are on the train or standing in line at the queue. These youth are not going to select step by step to find the product so they are very much interested to by product. The more fresh content posted daily, the better chance a business has of getting on the first page of a search. Social media sites provide a means to keep content fresh, alive and active.

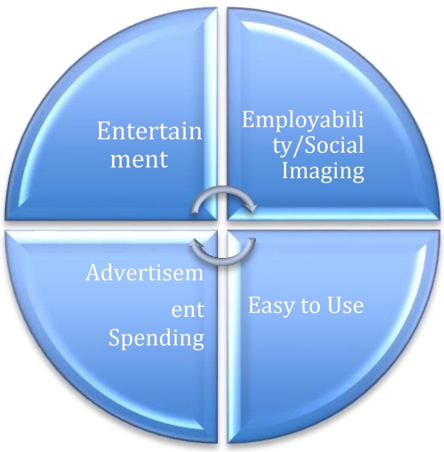


Fig 1. Consumer Buying Behavior among Youth

The buying behavior of a consumer will be affected by their families and by the opinions of their family members. Most of the times the youth are spend their time in online mobile. The traders are used it for their business to share the products through advertisement. Whenever a group of people begins to live together, whether because they are related by blood or by marriage, their buying character will begin to stroke off each other. Nowadays purchasing goods through Social sites helps the youth to be an entrepreneur. The fastest way to advertise anything is to upload it on social sites. Social media is faster in conveying the news or information than any other media say radio, television or newspapers.

Evaluating the amount of research that surrounds the usage of social networking sites in the consumer behavior of youth, it is important to determine whether or not, have these sites led to any impact on student rendezvous and achievement. This case work will be therefore able to review the available study and present both the positive and negative impacts of youth buying behavior through Social media networking on the most high in demand segment of our society.

To analyze the data which are collected from the youth in and around Theni district using data Mining technique. Data mining is the process of wide perspective and summarizing it into useful information performed through tasks like clustering, classification, associative relative method and so on. Through the process of classification, the attributes that might lead to this fascination is established.

II. LITERARTURE REVIEW

Jamaluddin Ibrahim, Rafidah Chee Ros, Nurul Faatihah Sulaiman, Roszaini Che Nordin & Li Ze was stated that the positive impacts of using Smartphone applications for online business processes. The result of the analysis was help to improve the business through technology. [1]

This research paper tries to represent, social networking sites such as Facebook, MySpace and Twitter are gaining popularity with the pace of time and due to their attractive features the youth of today's generation is spellbound towards them. The study argues against the notion claiming that due to the rapid popularity of social networking sites the youth tends to distract themselves from their studies and professions but on the contrary is also developing friendly and social ties with the world that revolves around them [2].

This paper reviewed the fact that out of all the respondents targeted, nearly 55.4% of the total population from people ranging in the age group 15 to 25 use social networking sites and also states that most of the users from the same age group use these sites as a medium to seek entertainment. In terms of gender division, male users are more as compared to female users wherein male users generally derive knowledge based information from these sites. It focuses on the fact that most of the youth uses these sites due to influence of their friends and just because their friends have been using and accessing these sites. This also illustrates the academic performance of students using social networking sites. Students acquiring 3.0 to 3.5 GPA in examinations are most inclines to these sites for entertainment [3].

The reviewer can read the 13 publications studied the use of social media as a marketing tool. The early studies here (2010–2013) explored consumer purchase behaviour and firm tactics, such as involving consumers in marketing strategies (for instance, García-Crespo et al. 2010; Goh et al. 2013). The later studies (2015–2016), however, became more focused on studying social commerce across networking sites such as Facebook, MySpace, and YouTube (e.g., Chen et al. 2015; Sung et al. 2016). Ten studies were interested in online communities and blogging (see Singh et al. 2014; Dennis et al. 2016). These were mostly interested in blogger behaviours, reader retention, online content, contributing capacity, and blog visibility (2011–2016). Nine publications revealed the risks associated with the use of social media. These are either very early studies (2008–2010; for instance, Tow et al. 2010) or fairly recent (2014–2016) learning about scamming and farcing issues faced by users. They focus on combating issues of privacy and security, whilst trying to differentiate between fake and authentic online content (for instance, Zhang et al. 2016) was found the final review of the above papers.

Nowadays, social networking sites and social media have increased in popularity, at a global level. For instance, Facebook is said to have more than a billion active users (as of 2012) since its beginning in 2004 (www.facebook.com). Social networking sites can be described as networks of friends for social or professional interactions (Trusov, Bucklin, & Pauwels, 2009). Indeed, online social networks have profoundly changed the propagation of information by making it incredibly easy to share and digest information on the internet (Akrimi & Khemakhem, 2012) the author found the positive impact of the purchase behaiour. [4]

The exclusive aspects of social media and its enormous popularity have revolutionized marketing practices such as advertising and promotion (Hanna, Rohm, & Crittenden, 2011). Social media has also influenced consumer behavior from information acquisition to post-purchase behavior such as dissatisfaction statements or behaviors (Mangold & Faulds, 2009) and patterns of Internet usage (Ross et al., 2009; Laroche et al., 2012). [5]

Use behaviour was examined across a variety of platforms like Facebook, Twitter, MySpace, and Flickr for purchase the new trendy items through social media network.

III. RESEARCH METHODOLOGY

A. Objective

The basic objective of the paper is to understand the usage of social media among youth buying behaviour in the city of Theni. It also aims at assessing the power of social media on the consumer buying behaviour. The study also explores the preference of the youngsters regarding various social media web sites.

B. Data Collection

Primary data was collected through a structured questionnaire that was distributed among youth in city college students of Theni. The questionnaire contained multiple choice questions as well as it also incorporated various parameters that were identified for analysing the preferences of youngsters towards buying behavior of various social media websites. Primary research was done through distribution of structured questionnaires amongst 115 youth in the city college students of Theni.

C. Tool Used for Analysis:

The research is basically focused on the understanding the usage prototype of youth buying behavior and their preference towards various social media networking sites. The data was analysed by using R tool. Finally, Find the highly impact social media networking sites for the buying behavior of the youngsters.

D. Data Analysis

Algorithm used:

KMeans algorithm is used to find the result of the purchase strategy of the youth.

Cluster Analysis in R

R has an amazing variety of functions for cluster analysis. In this section, we use three of the many approaches: hierarchical agglomerative, partitioning, and model based.

Data Preparation: Prior to clustering data, you may want to remove or estimate missing data and rescale variables for comparability.

```
# Prepare Data
    mydata <- na.omit(mydata) # listwise deletion of
    missing
    mydata <- scale(mydata) # standardize variables
```

Partitioning: K-means clustering is the most popular partitioning method. It requires the analyst to specify the number of clusters to extract. A plot of the within groups sum of squares by number of clusters extracted can help determine the appropriate number of clusters. The analyst looks for a bend in the plot similar to a screen test in factor analysis.

```
# Determine number of clusters
wss <- (nrow(mydata)-1)*sum(apply(mydata,2,var))
for (i in 2:15) wss[i] <- sum(kmeans(mydata,
  centers=i)$withinss)
plot(1:15, wss, type="b", xlab="Number of Clusters",
 ylab="Within groups sum of squares")
# K-Means Cluster Analysis
fit <- kmeans(mydata, 5) # 5 cluster solution
# get cluster means
aggregate(mydata,by=list(fit$cluster),FUN=mean)
# append cluster assignment
mydata <- data.frame(mydata, fit$cluster)
```

A robust version of K-means based on mediods can be invoked by using pam( ) instead of kmeans( ). The function pamk( ) in the fpc package is a wrapper for pam that also prints the suggested number of clusters based on optimum average silhouette width.

Hierarchical Agglomerative: There are a wide range of hierarchical clustering approaches. I have had good luck with Ward's method described below.

```
# Ward Hierarchical Clustering
d <- dist(mydata, method = "euclidean") # distance matrix
fit <- hclust(d, method="ward")
plot(fit) # display dendogram
groups <- cutree(fit, k=5) # cut tree into 5 clusters
# draw dendogram with red borders around the 5 clusters
rect.hclust(fit, k=5, border="red")
```

The pvclust( ) function in the pvclust package provides p-values for hierarchical clustering based on multiscale bootstrap resampling. Clusters that are highly supported by the data will have large p values. Be aware that pvclust clusters columns, not rows. Transpose your data before using.

```
# Ward Hierarchical Clustering with Bootstrapped p
values
library(pvclust)
fit <- pvclust(mydata, method.hclust="ward",
  method.dist="euclidean")
plot(fit) # dendogram with p values
# add rectangles around groups highly supported by
the data
pvrect(fit, alpha=.95)
```

Model Based: Model based approaches assume a variety of data models and apply maximum likelihood estimation and Bayes criteria to identify the most likely model and number of clusters. Specifically, the Mclust( ) function in the mclust package selects the optimal model according to BIC for EM initialized by hierarchical clustering for parameterized Gaussian mixture models. One chooses the model and number of clusters with the largest BIC.

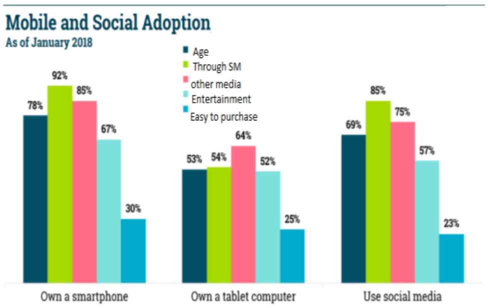
```
# Model Based Clustering
library(mclust)
fit <- Mclust(mydata)
plot(fit) # plot results
summary(fit) # display the best model
# K-Means Clustering with 5 clusters
fit <- kmeans(mydata, 5)
# Cluster Plot against 1st 2 principal components
# vary parameters for most readable graph
library(cluster)
clusplot(mydata, fit$cluster, color=TRUE,
shade=TRUE,
  labels=2, lines=0)
# Centroid Plot against 1st 2 discriminant functions
library(fpc)
plotcluster(mydata, fit$cluster)
# comparing 2 cluster solutions
library(fpc)
cluster.stats(d, fit1$cluster, fit2$cluster)
```

Where d is a distance matrix among objects, and fit1$cluster and fit$cluster are integer vectors containing classification results from two different clustering of the same data.

Analysis of Data

The researcher collects more than 500 responses from samples all over Theni district. She spent nearly 2 months to collect the fresh data from end users. After collecting the information, all the details are fed into the software and checked for outlier. The cleaned data was analyzed using single attribute and multiple attributes. Gender, Qualification of the respondents, Type of the serial they are watching, Total number of serials, Total hours they spend for their serials are considered as single attributes of the study.

To process the data, I have installed the following libraries such as pvclust, mclust, cluster, fpc and NBClust from cloud storage. Then the dataset was inserted into the R tool for processing.



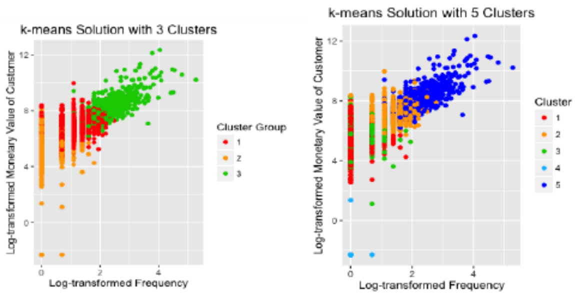


Fig 1. K-Means Solution with 5 Cluster

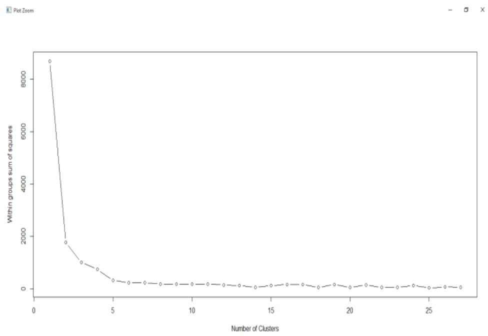
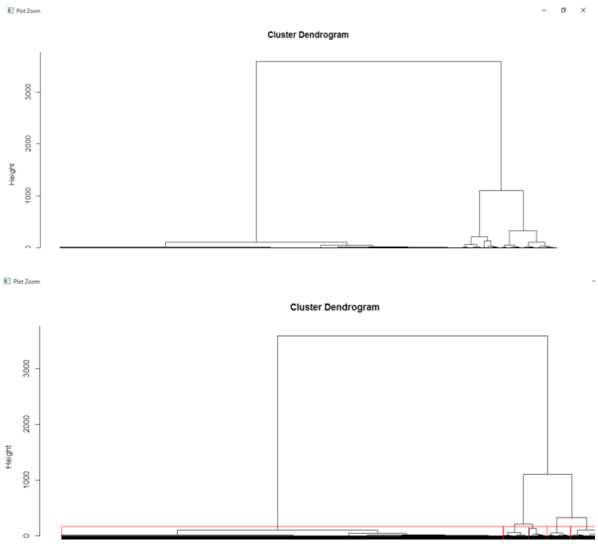


Fig 2.Number of Cluster



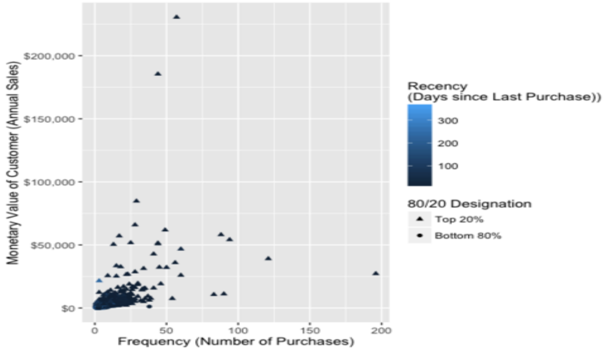


Fig 3. Cluster group

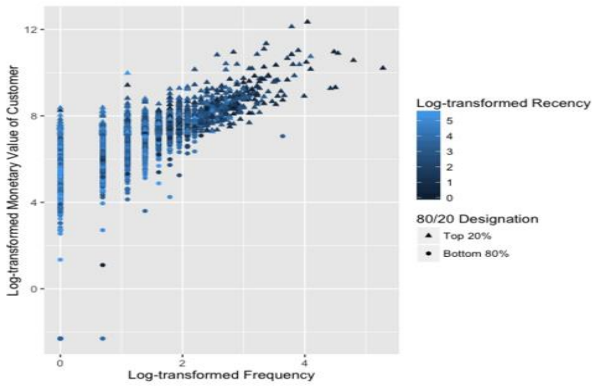
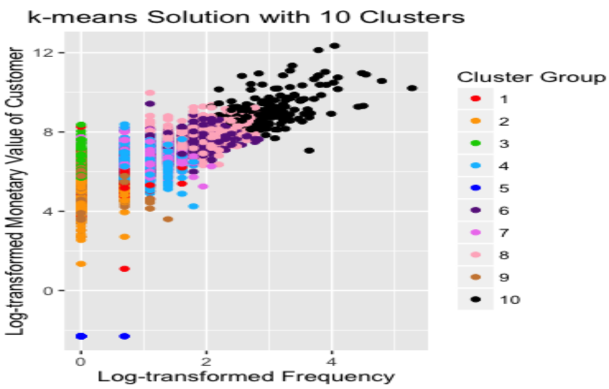
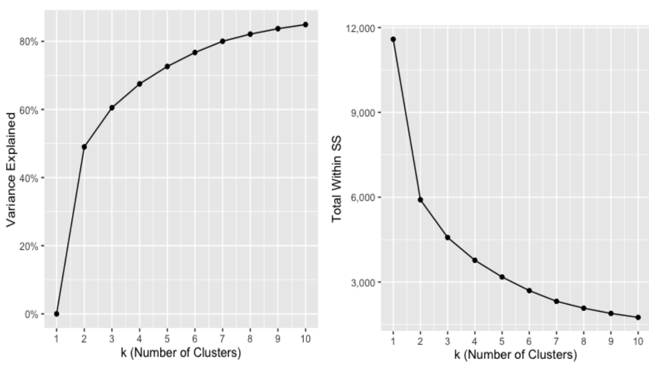


Fig 4. Log Transformed Frequency





IV. CONCLUSION

This research paper has classified the purchase behavior into two segments in terms of the shopping factors. C1(Cluster1) consists of relatively higher rate of purchase service class people and C2 has younger students. The predecessor factors contributing shopping experience influence both the segments. However, the extent of persuade differentiates the two segments on some factors. This provides a better understanding of each segment and helps social media dependent purchase in identifying the youth and deciphering the impact of those on each of the sector. Defining shopping experience needs growing manifestation of various antecedent factors. Shoppers across both the segment desired the presence all multiple factors that include ambience, physical infrastructure, convenience and safety.

REFERENCES

[1]. Babin, B. J., Darden, W. R., & Griffin, M. (1994). Work and/or fun: Measuring hedonic and utilitarian shopping value. Journal of Consumer Research, 20, 644–656. https:// doi.org/10.1086/209376

[2]. Brito, P. Q. (2009). Shopping centre image dynamics of a new entrant. International Journal of Retail and Distribution Management, 37(7), 580–599. https://doi. org/10.1108/09590550910964611

[3]. Casabay´o, M., Agell, N., S´anchez-Hern´andez, G., 2015. Improved market segmentation by fuzzifying crisp clusters: A case study of the energy market in Spain. Expert Systems with Applications 42, 1637–1643.

[4]. Chapman, C., Feit, E.M., 2015. R for marketing research and analytics. 1 ed., Springer, New York, NY. Chaturvedi, A., Carroll, J.D., 2001. Deriving market structures via additive decomposition of market shares (application of three-way generalized SINDCLUS).

[5]. Chaturvedi, A., Carroll, J.D., 2006. CLUSCALE ("CLUstering and multidimensional SCAL[E]ing"): A three-way hybrid model incorporating overlapping clustering and multidimensional scaling structure. Journal of Classification 23, 269–299.

[6]. Chaturvedi, A., Carroll, J.D., Green, P.E., Rotondo, J.A., 1997. A feature-based approach to market segmentation via overlapping k-centroids clustering. Journal of Marketing Research 34, 370–377.

[7]. France, S.L., Ghose, S., 2016. An analysis and visualization methodology for identifying and testing market structure. Marketing Science 35, 182–197.

[8]. France, S.L., Vaghefi, M.S., Zhao, H., 2016. Characterizing viral videos: Methodology and applications. Electronic Commerce Research and Applications 19, 19–32.

[9]. Frank, R.E., Green, P.E., 1968. Numerical taxonomy in marketing analysis: A review article. Journal of Marketing Research 5, 83–94. Frank, R.E., Massy, W.F., Morrison, D.G., 1965. Bias in multiple discriminant analysis. Journal of Marketing Research 2, 250–258.