Impact of Social Media Usage on Emotional Imbalance

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Abstract

It is no surprise that social media has a huge impact on us, given the ever-increasing rate of its rampant use in the contemporary world of digitalization. With toddlers being adept in the know-how of mobile phones and tablets, to school and college students relying on social media platforms for socializing, to adults (and even older adults) utilising social media to expand their personal as well as professional growth… the list is indeed never-ending. Given this surge of technological invasion in our daily lives, the influence of social media platforms can hardly be neglected. The present study attempts to identify and understand different aspects of an individual's behaviour due to social media usage. The study has examined negative emotions such as worry, depression and anxiety resulting from using social media and finally segments the respondents on the basis of these factors. Multivariate cross-sectional data was analysed using supervised and unsupervised algorithms. The researchers assessed various aspects of the psychological changes in an individual due to social media usage. The study concludes that there are five important factors an individual experiences using social media - Feelings, Time Spent, Obsession, Other activity Engagement and Stress Buster. The results indicate that people use social media primarily for social networking. Stepwise multiple regression resulted in a model where feelings and time spent, two prominent factors with reference to social media usage, proved statistically significant in arising negative feelings or emotional imbalance in an individual. The factors were also used to identify different segments of respondents using cluster analysis. The clusters of respondents were named as Sensitive, Balanced Emotions and Fanatical Emotions.

Key words: *Social Media, Emotional Imbalance, Multivariate Data Analysis*

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Introduction

Over the past two decades, humanity has used various forms of communication, which, in turn, has evolved over the years. Over this period, we have moved rapidly from using the landline and hoping someone answers, to being able to communicate with friends and family at any time while being aware of their location and presence on various communication applications. This has been possible only because people want to disclose their whereabouts, activities and feelings.

Today, social media has become an integral part of nearly everyone's social life. Social media is also used as a second screen while watching sports or advertisements on TV (Jain, 2015). Using structured observations, in-depth interviews and netnography, the researchers discovered that sports viewers connect and interact on social media; they use Twitter for interactions, Facebook for private interactions, Instagram for personal pictures and Pinterest for trendy and stylish pictures. The study reveals how social media impacts people's emotional health and how best to manage both the positives and negatives. It is no surprise that social media has created a huge impact on the individual's lifestyle, given the ever-increasing rate of its widespread use in the contemporary world of digitalization. With toddlers being skilled in the know-how of mobile phones and tablets, to school and college students' dependence on social media platforms for socializing, to adults (and even older adults) employing social media to expand their personal as well as professional growth… the list is endless. Given such a surge of technological conquest within each individual's daily life, its influence can barely be ignored.

Although, the usage of social media has tremendous scope if applied optimally in the direction of increasing accessibility and growth in a variety of opportunities of development, the potentially adverse effects of the same are widely talked about. Social networking sites and social media platforms have a major impact on the individual's emotional health. The study lists some aspects that can help explore the impact of social media on social and emotional development. Social media is an emotional vocabulary building tool. With each new update on popular social networking platforms, numerous emoticons are provided to choose from to communicate with others. Such a wide range of emoticons helps people express themselves in more vivid and diverse ways. However, one needs to be cautious about too much reliance on such tools replacing real-life expressions.

Emoticons cannot be a substitute for face-to-face interactions. While such emoticons can play a significant role in developing and enhancing the emotional vocabulary, it is also important to note that such emoticons are also subject to an individual's perception. Therefore, excessive use of such tools of emotional expressions can hinder an individual's ability to recognise the emotional reactions of others as compared to face-to-face interactions.

Social media is used to develop one's social identity. Social media is evidently intended to be used as a tool to connect with others across the globe, transcending not just geographical boundaries, but also reaching out to unfamiliar people sharing similar interests. At the same time, it also serves as a platform to express feelings and experiences of a person online. More importantly, it is crucial to note that such an identity is almost on an off-and-on basis, which adds an unreal and superficial aspect to the social identity formed.

Social media is a channel for negative emotions. With greater accessibility to the internet, social media platforms are increasingly being used as outlets to express negative emotions. This is especially true because such platforms are perceived as a safe outlet, wherein individuals are given the freedom to express themselves. Further, angling has become a prevalent phenomenon, wherein individuals express themselves under the safety net of anonymity.

Social media can be considered as a source of emotional dependence. In case of children and youngsters, social media platforms are considered to be the deciding factor for their social status, or popularity, be it the number of friends or followers, or the number of likes their posts or updates attract. The social as well as emotional identity of these people appear to be dictated by such platforms. Instead of focusing on one's emotional experiences, youngsters are using social media platforms to update their status that reflects the way they are feeling at a particular time.

Social media has reduced our threshold for tolerance. Expressing our emotions on social media can reduce our ability to tolerate distress. Social media is so convenient that it has increased our expectations. We want an immediate response to our posts; if we don't get this, it could become a source of frustration.

Review of Literature

Review of related literature will help to understand the link between social media and emotions, which may further be categorized as positive emotions, negative emotions, depression, and anxiety related to social media. In the past, many researchers have shown keen interest in studying the impact of social media on the emotional balance of an individual. The present section gives a brief review, the findings and suggestions. Though, the availability of the research work on the topic is extensive, the review of the latest work has been presented here. The literature review on the existing topic is significant in the sense that it gives a basis to formulate the problem and search the areas of research.

Research on studying the impact of social media on an individual's emotional balance has been conducted in different regions and countries. Some are briefly reviewed in the present section.

Jalonen (2014) had attempted to review the negative emotions in social media. The author has emphasised that the companies should have an awareness of the emotional tone of social media discussions related to their products, services and brands.

The study was conducted in Turku, Finland and focused on descriptive research to ensure that it was relevant to the purpose of the paper in terms of the subject matter, theoretical framework, methodology, and empirical findings. A great deal of social media behaviour has a negative bias, which indicated that a recall of unpleasant memories was higher as compared to positive memories. It also meant that there was a high likelihood that people were recognized and influenced by negative information shared on social media. To understand negative emotions with reference to social media, the author identified six factors using descriptive and inductive technique. The conclusion of the study indicated that an emotionally intelligent organization must develop the ability to recognise the emotions shared and diffused in social media, understand their meaning for the business and behave based on that understanding.

Bashir and Bhat (2017), in their research paper "Effects of Social Media on Mental Health: A Review", studied the effects of social media on mental health, especially on younger children. Their study revealed that the younger generation is vulnerable. Younger people are at the growing stage of life and at higher risk of serious mental health problems. The study attempted to identify the relations between usage of social media and mental health, which determined the significance of the topic. The problems identified were online harassment, depression, sexting/texting, stress, fatigue, loneliness, and decline in intellectual abilities, emotion suppression and lack of concentration. The younger generation went through these negative emotions, which impacted their mental health directly or indirectly. The review paper also suggested ways to reduce the risk associated with using social media. Suggestions included conducting awareness programs, setting an age limit for accessing social networking sites and conducting counselling sessions for younger children.

Hunt *et al.* (2018) conducted an experimental study to investigate the potential causal role that social media played in linking social media use to deterioration in well-being.

The study was conducted on 143 undergraduates at the University of Pennsylvania to determine their mood and well-being in relation to their activities on social media. For this, screen shots of a week's worth of their social media activity through their smartphones was used as data for the study. The researchers found that the group that used social media in a limited manner showed significant reduction in loneliness and depression over three weeks compared to the control group. Both groups showed a significant decrease in anxiety and fear of missing out over baseline, suggesting a benefit of increased self-monitoring. The findings of the study suggested that if the social media usage is limited to approximately 30 minutes per day, it may lead to a significant improvement in well-being.

Vogel *et al.* (2015) studied the relationship between social comparison orientation, Facebook use, and negative psychological outcomes. The researchers conducted two studies. Study 1 used the correlation approach and revealed that participants high (vs. low) in social comparison orientation exhibited heavier Facebook use. Study 2 used an experimental approach and revealed that participants high in social comparison orientation had poorer self-perception, lower self-esteem, and more negative affect balance than their low-social comparison orientation counterparts after engaging in brief social comparisons on Facebook.

According to **Dabbagh and Kitsantas (2012),** Personal Learning environment (PLE) was an encouraging approach for both formal and informal learning using social media. The approach supported the students in self-regulated learning in higher education context through social media. The objective of the study was to theorize the connection between Personal Learning Environment (PLE), social media and self-regulated learning and provide a three-level pedagogical framework for using social media to create PLEs that support student self-regulated learning. A Personal Learning Environment (PLE) was a possibly promising pedagogical approach for both assimilating formal and informal learning using social media and supporting student self-regulated learning in higher education settings.

Davis *et al.* (2004) studied a theory-driven, multidimensional measure of problematic Internet use: The Online Cognition Scale (OCS). A confirmatory factor analysis indicated that problematic Internet use consists of 4 dimensions: reduced impulse control, loneliness/depression, social comfort, and distraction. As hypothesized, the OCS predicted all the study variables in the expected directions. The study listed procrastination, impulsiveness and social rejection as key elements of problematic internet use. OCS was used for both clinical assessment of Internet addiction and as an organizational pre-employment screening measure to identify potential employees who are likely

Saleem *et al.* (2014), in their research paper "Facebook causes loneliness among higher learning students in Pakistan," studied a sample of 600 students from different institutes. Pakistan being the 27th most populated country on Facebook (2010), generated approximately 44,000 new user id's every week. The negative impact showed that addiction to Facebook resulted in deterioration of sleeping habits, health, interest in studies and created loneliness. After using the two scales: UCLA loneliness scale and Facebook addiction test, research confirmed that there was a linear and positive correlation between Facebook addiction and its effect on loneliness among higher learning students and users were more likely to feel lonely due to extensive use of it.

Bruggeman *et al.* (2016), studied whether Digital media had an effect on the psychological wellbeing of children aged 9 to 12. Data was collected from 13,871 students from over 163 primary schools located in the province of Antwerp, Belgium through a questionnaire (consisting of 72 questions) based on the 5-point Likert scale. Data was collected to assess subjective well-being in terms of Happiness, Digital media use through Frequency of use and Reasons for using social media. It also contained additional questions on Facebook usage and their Social relationships - both online and offline. Result shows there was a direct, but significantly weak relationship between digital media use and psychological wellbeing. It was concluded that in the specific group of children having a Facebook profile, the use of Facebook was only modestly related to psychological well-being. Conversely, the offline social network was much more effective. The paper discussed how children used social media presently and how they would use it in future, which could have a positive, or a negative impact. A possible positive effect was that children who already are exposed to digital media at an early age are likely to learn to deal with it at a young age and therefore might become more resistant to possible negative effects in later life, such as internet addiction. On the other hand, it might also be presumable that an early starting age of too much digital media use, similar to alcohol addiction (Gruber, DiClemente, Anderson, & Lodico, 1996), was expected to lead to a persistent habit in the long term.

Thorisdottir *et al.* (2019), analysed population survey data collected from Icelandic adolescents to chalk out the connection between usage of social media and active and passive users over different social media platforms like Instagram, Facebook and Snapchat. The study included students aged 14-16 years by providing them with anonymous questionnaires which measured the usage of time spent on social media, different types of social media used, etc. Active users and Passive users were defined as - active users were those who spent a lot of time on the internet including chatting and networking with unknown people while passive users were those who were introverts and preferred surfing and stalking/ viewing others' profile. Different indicators were measured at a 4-point scale to 8-point scale and general questions like parental support and self-esteem helped the research paper to analysis their behaviour in depth. The data was analysed using the hierarchical linear regression model and revealed that passive social media use was related to greater symptoms of anxiety and depressed mood among adolescents and active social media use was related to decreased symptoms of anxiety and depressed mood, even after controlling for time spent on social media. The result indicated that passive users were significantly inclined towards anxiety and depressed moods, especially among girls, and active users showed decreased symptoms of anxiety and depressed mood.

Wu *et al.* (2015), reviewed the link between social connectedness and internet technology use by adolescents and their mental health. Internet technology referred to the utilization of electronic devices for interpersonal interactions and communications (**Mistler-Jackson and Songer, 2000**). The term 'social connectedness' was used to refer to interaction and socializing with family and friends over an internet-based app. Socializing had shifted from one-to-one meetings to online platforms. The five online databases used for a systematic review of the literature were CINAHL, ERIC, Psychology and Behavioural Sciences Collection, Science and Technology Collection and the refined EBSCO Social Sciences database. The research revealed that an adolescent's sense of being connected had increased due to increased use of Internet technology and adolescents were using social media for their own benefit.

McCrae *et al.* (2017) studied the relationship between social media use and depressive symptoms in the child and adolescent. A systematic search was conducted from the Medline, PsycInfo and Embase databases which brought out eleven suitable studies. The results found to be relevant were pulled out from each study, resulting in a total sample size of 12,646. After analysing the literature, it was revealed that there exists a correlation between social media use and depressive symptoms in children. In fact, the correlation was small, but it was found statistically significant.

There are a number of studies conducted to identify a link between time spent using social media and mental health issues, such as depression and anxiety. However, the number of longitudinal studies which examine association between time spent using social media and mental health, is limited. In some research, social media was forecasted to result in higher levels of mental health issues in the years to come (**Coyne *et al.*, 2019; Vannucci, Flannery, & Ohannessian, 2017**), while in other research studies, mental health projected usage of social media (**Scherr, Toma, & Schuster, 2018**). Furthermore, some studies also found bi-directional longitudinal relationships between social media and mental health (**Frison, & Eggermont, 2017; Houghton, et al., 2018; Nesi, Miller, & Prinstein, 2017**). Research by **Twenge, Joiner, Rogers, and Martin (2018)** was the most influential research on this topic and examined generational differences regarding media use and the number of adolescents.

Heffer *et al.* (2018) studied the longitudinal association between social media use and depressive symptoms among adolescents and young adults. Social media, the fastest growing platform, had taken a toll on the life of humans. While it had some positive outcomes, there were negative ones too. It helped to connect an individual with his peers, friends, colleagues, etc. The study was done on 594 adolescents and 1,132 undergraduate students over the period of 2 years and 6 years annually. Different procedures were used to know the usage of social media, screen and non-screen activities. Using standard deviation and Autoregressive Cross-lagged Model results revealed no such relationship between social media usage and depressive symptoms in both the categories. However, symptoms like depression were predicted to be more frequent through usage of social media among adolescent girls only.

Coyene *et al.* (2019) conducted an 8-year longitudinal study examining the association between time spent using social media and depression and anxiety at the intra-individual level. Participants between the ages of 13 and 20 were made to fill in a questionnaire once each year. Among the participants, 500 were adolescents. Results revealed that increased time spent on social media was not associated with increased mental health issues when examined at the individual level. Hopefully these results can move the field of research beyond its past focus on screen time.

There is rising concern about the impact of the internet on mental health among youngsters. This topic has found frequent coverage in mass media. **Kraut *et al.* (1998)** and **Young and Rodgers (2009)** found early evidence of adverse psychological impact from frequent internet use, which raised the risk of depressive symptoms. Later studies similarly revealed that there was a relationship between online activity by younger people and feelings of low self-esteem **(Caplan 2002)**, loneliness **(Clayton *et al.*, 2013)**, self-harm **(Lam *et al.,* 2009)** and autistic traits **(Finkenauer et al. 2012)**. However, other studies revealed a reverse situation where social media use resulted in higher self-esteem and satisfaction with life, and reduced risk of mental health problems **(Valkenburg et al., 2006; Bessièrre et al., 2008; Grieve *et al.*, 2013; Best et al., 2014)**. **Wu *et al.* (2016)** found that development of connectedness, supportive social bonds and belongingness can protect against adversities such as isolation and maltreatment.

Several viewpoints have been proposed for the presumed link between social media use and emotional problems in younger people. In the progression from youth to adulthood, socializing has become essential, and use of social media may have deep influence on this aspect **(Wood *et al.,* 2016)**. Applying John Bowlby's psychoanalytic theory, **Oldmeadow *et al.* (2013)** stated that it was more likely that people turn to Facebook for emotional support if they had attachment apprehension. However, reduced face-to-face contact used in the traditional supportive environment is an undesirable phenomenon since it can help young people to manage the challenges of teenage years. Development of self-awareness may be encouraged in young people who lack engagement in reflective interactions with family and friends **(Siegel 2014)**. Empathy as practised through social relationships may not be as close and expressive online, where superficial behaviour such as virtue-signalling prevails.

The researchers of the present study extended their research across a number of research papers, which helped them understand the impact of social media on the minds of an individual and resulting emotional imbalance. The research conducted earlier mainly focused on the conceptual views about the topic and review. The papers based on empirical work indicated the positive as well as negative effects of internet and usage of social media on the mental and physical health of an individual. Using social networking sites and resulting addiction characterises an emerging issue in psychiatry research, and as with other potentially related ailments, many problems still remain unanswered. The present study attempts to identify a connection between social media and the emotional imbalance due to high use especially among teenagers and youngsters. The focus of the research is on the emotional connect youngsters develop while using Social Media.

Hypothesis of the Study

The present study seeks to establish the link between the usage of social media and emotional imbalance.

Objectives

The objective of the study is to examine the relationship between usage of social media and emotional balance, and to segment the respondents based on the factors so identified.

In order to examine the impact of social media usage and further segmentation of the target group of respondents, the study includes the following objectives:

- To identify the factors of understanding different aspects of behaviour an individual experiences due to social media usage.
- To study the impact of factors so emerged due to usage of social media on negative emotions such as worry, depression and anxiety.
- To segment the respondents in clusters on the basis of factors of emotional imbalance so emerged.

Hypotheses

The alternative hypotheses from the objectives were as follows:

H_{01}: There is a relationship between negative emotions such as worry, depression and anxiety with the factors of emotional imbalance while using social media such as Feelings & Experience, Time Spent, Social Media Effects, Activities and Stress Buster.

Multiple Regression Hypothesis

H_{02}: *$\beta_i = 0$ for all i= 1, 2, 3, 4 and 5*

H_{12}: *$\beta_i \neq 0$ for all i= 1, 2, 3, 4 and 5*

The model under consideration is shown in Figures 1 and 2.

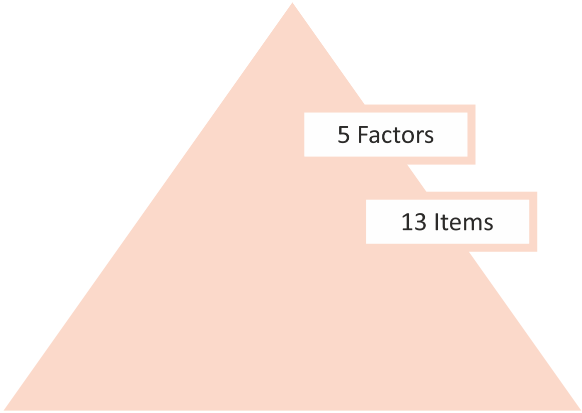


Figure 1: Pyramid of Factors of emotional description while using social media

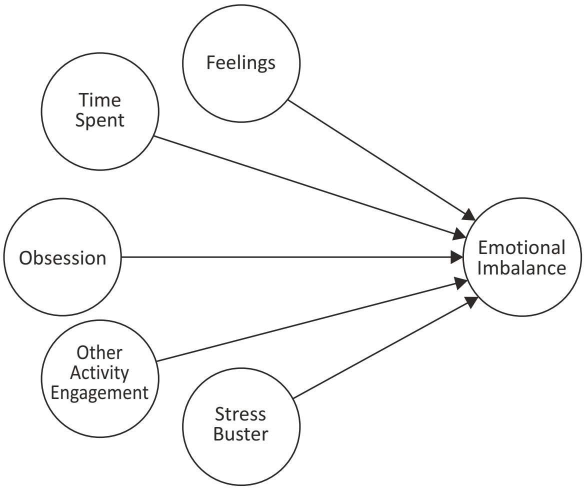


Figure 2: Proposed Model

Research Methodology

The study adopted a cross sectional descriptive research design in order to accomplish the research objectives to examine the relation between usage of social media and emotional imbalance and to segment the respondents based on the factors so identified. The population of the study comprises of youngsters living primarily in urban and semi-urban areas. The study was conducted among students and professionals in the age group of 18 to 35 years with the mean age of 28 years. Most of the respondents (more than 60 percent) used social media very often in a day.

A self-designed questionnaire based on past literature was developed, which comprised of demographic profile and multi-item five-point Likert scale anchored by 5 = Very often (high frequency, best value) and 1 = Never (lowest frequency, poorest value). The questionnaire was administered on 150 respondents and completed responses were received from 104 respondents. Correlation analysis was used to determine the direction and strength of the relationship between variables. Multiple Regression analysis was used to examine the relationship between multiple variables. **Bohorquez *et al.* (2019)** conducted the principal component analysis at the initial stage so that contributions of the selected variables to variance within the chosen data set could be verified and then performed a k-means analysis as a partitional clustering method using Euclidean Distance to establish clusters among the finalized list of explanatory variables. On the same lines, the present study attempted to apply exploratory factor analysis to reduce the number of variables in the study. Cluster analysis was employed to segment the respondents based on the summated scale of factor analysis using SPSS ver. 20.

Sample Selection

A sample of urban professionals and students in the age group of 18 to 40 years was selected for the research. The sample was based on non-probability sample based on judgement that the sample represented the demographic profile considered for the research. Respondents were based in two metropolitan cities, three Tier II and two Tier III cities in India.

Period of the Study

The study was conducted during the period of March and September 2019.

Results

The current study revealed usage of social media as follows: the highest, 83 of 104 respondents used it for social networking and second highest, 70 of 104 respondents, used it for browsing purposes. The reliability of the questionnaire was tested through Cronbach's Alpha, having value of 0.701, hence, found satisfactory.

Table1: Reliability Statistics

Cronbach's Alpha	No of Items
.701	20

Source: Authors' calculation

Exploratory factor analysis was employed to identify the important factors while using social media. Since too many trivial variables could be cumbersome, it made sense to focus on some key factors and hence, factor analysis was used to place variables into meaningful categories **(Yong and Pearce, 2013).** Factor analysis is used in many other situations such as data transformation, hypothesis-testing, mapping, and scaling (Rummel, 1970). To understand whether the perceptions can be "grouped" and to see the big picture in terms of understanding emotional imbalance of an individual due to social media, reduce the 13 variables to a smaller number. R-type factor analysis is applied to understand the perceptions of variables which were measured in metric scale. It is inspected from the correlation matrix that 13 out of 25 correlations (52%) are significant at 1% level (Appendix Table 2), hence, adequate basis for proceeding to an empirical examination of adequacy for factor analysis.

The overall significance of the correlation matrix is checked with the **Bartlett test** and factorability of the overall set of variables and individual variables using the **measure of sampling adequacy** (MSA) (Table 2).

Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.617
Bartlett's Test of Sphericity	Approx. Chi-Square	294.944
	Df	78
	Sig.	.000

Source: Authors' calculation

To test the overall interdependency of variables, Kaiser Meyer Olkin measure of sampling is calculated and from Table 2, it is noted that the value of KMO is 0.617. Since the value of KMO is more than 0.5, all the 13 variables corresponding to factors affecting the emotional imbalance of an individual through use of social media can be considered for factor analysis. Also, Bartlett's test is highly significant showing that the null hypothesis that original correlation matrix is an identity matrix is rejected. This indicates that *R*-matrix is not an identity matrix and hence, there exists a desirable level of interdependency in the data. Hence, KMO and Bartlett's tests are favourable to carry factor analysis further.

The factor analysis is interpreted on the basis of rotated factor loadings, rotated Eigenvalues, and Scree test **(Yong and Pearce, 2013)**. According to latent root criteria of retaining factors with Eigenvalue greater than 1 (Table 3, Appendix), five factors will be retained. The Scree plot (Figure 1, Appendix) also indicates that 5 factors may be appropriate. The five-factor retained represent 66.12% of the variance of the 13 variables, deemed significant in terms of total variance explained. Combining all these criteria together leads to the conclusion to retain five factors for further analysis.

Factor analysis using principal component method with varimax rotation was applied on 13 variables; the results revealed through factor analysis that there are five factors that affect the emotional imbalance of an individual due to social media use. The individual factors along with its variables, factor loading, and percent variance explained are detailed in Table 3.

Table 3: Factor loading with percentage variance explained

S.N.	Factor Name	Item	Factor load	% variance explained
1	**Feelings & Experience**	How often have you been bothered by feeling down, depressed, irritable or hopeless over the internet?	0.736	**21.5**
		How often have you ever experienced feelings of sadness as a result of using social media?	0.73	
		Have you ever experienced feelings of isolation as a result of social media?	0.722	
		Have you ever been diagnosed with depression due to excessive use of social media?	0.499	
		How often do you get upset by people's reaction to your post?	0.497	
2	**Time Spent**	How often do you spend your time on social media?	0.88	**16**
		How often do you visit social media?	0.854	
		How often do you prefer having conversation on social media?	0.494	
3	**Obsession**	You feel proud telling people that yo u are using social media?	0.81	**11.5**
		Would you be upset if any Social Media shuts down?	0.78	
		Your Facebook, Instag ram and Snapchat is always logged in your mobile, computer and other devices?	0.518	
4	**Other Activity Engagement**	How often do you prefe r playing outdoor games or mind related activities other than using Social Media?	0.879	**9**
5	**Stress Buster**	How frequently does social media reduce your stress levels?	0.702	**8**
		Cumulative Variance		**66**

Source: Authors' calculation

Factor 1: Feelings

The items under the factor 'feelings' show the way individuals feel about social media. Their experience, reaction on posts, depression due to excessive use, irritation, etc. lead to emotional imbalance. There is 21.5% of variation explained in the factor 'feelings'.

Factor 2: Time Spent

This factor shows the amount of time spent, number of visits and preference of an individual on social media. This factor explains 16% of variation.

Factor 3: Obsession

This factor includes the effects of social media on the individual. The factor explains 11.5% of variance.

Factor 4: Other Activity Engagement

This factor shows the frequency of an individual playing outdoor games or mind related activities other than using social media. These activities help relax and refresh the mind of an individual. There is only 9% of explained variation in this factor.

Factor 5: Stress Buster

This factor shows the frequency of the effect of social media on reduction of stress of an individual. This factor explains 8% of explained variation.

The factors so emerged are subjected to summated scale and used as independent variables to predict the emotional imbalance (negative emotions such as worry, depression and anxiety) score of individuals with an attempt of multiple regression model.

Multiple Regression Analysis

To understand the average strength of relationship between the factors emerged and emotional experiences of users, multiple regression model is applied. It helps to understand the ability of the independent variables to predict the dependent variable (**Anand *et. al*, 2017)**. The proposed multiple regression model is given by Equation (1).

$$Y = a + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + e \qquad \text{--- (1)}$$

where,

y = Negative emotions such as worry, depression and anxiety

x_1 = Feelings & Experience

x_2 = Time Spent

x_3 = Social Media Effects

x_4 = Activities

x_5 = Stress Buster

e = Error

Assessment of statistical assumptions is an important part before proceeding to fit the multiple regression model. Graphical analyses such as residual plots, partial regression plots and normal probability plots are used to assess assumptions for the variate **Hair *et al.* (2018)**. The plotted graphs (**Figures 2 and 3** Appendix) show that the scatter plot between the residuals and the predicted dependent values almost follow a null pattern; hence, there is no problem of heteroscadasticity i.e. error terms have constant variance. It follows a normal distribution as the normal p-p plot shows a straight diagonal line, and the plotted residual hovers closely around the line. The error terms also follow linearity.

The diagnostic tests for multiple regression also include multicollinearity test. The simplest means of identifying multicollinearity is to examine the correlation between independent variables as shown in Table 4. All the independent variables show a weak correlation or no correlation; hence, there is no problem of multicollinearity among the independent variables.

Table 4: Correlation between the independent variables

		Emotional imbalance	Feelings	Time_spent	Obsession	Other activities	Stress_buster
Pearson Correlation	Emotional imbalance	1.000	.355	.213	.118	.011	.125
	feeling_experience	.355	1.000	.086	.180	-.082	.147
	time_spent	.213	.086	1.000	.241	-.037	.292
	Obsession	.118	.180	.241	1.000	.091	.197
	Other activities	.011	-.082	-.037	.091	1.000	.024
	stress_buster	.125	.147	.292	.197	.024	1.000

Source: Authors' calculation

To assess both pairwise and multiple variable collinearity, the two common measures are tolerance and its inverse, the variance inflation factor (VIF) **Hair *et al*. (2018).** The tolerance is almost close to 1 (values more than 0.875) and VIF less than 1.42 (Table 5 Appendix) indicating multicollinearity is not a problem in this case.

The diagnostic tests indicate that the multiple regression model given in eq. (1) can be used to fit the model. Running the regression model in SPSS ver. 20 using least square method taking Method type as enter, it was found that some independent variables showed insignificant *t* values. To deal with such independent variables, the regression was re-run taking step wise regression as the type of regression method and the model summary was presented in Table 5. Referring to the output tables, the coefficient of determination was found low. The overall model is a good fit as *F* statistics was 9.607 (Table 5) with significance value less than 0.01.

Table 5: Regression Negative emotions (y) and Feelings & Experience (x_1) and Time Spent (x_2) Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.355[a]	0.126	0.118	3.10255
2	.400[b]	0.160	0.143	3.05756
a. Predictors: (Constant), x1				
b. Predictors: (Constant), x1, x2				
c. Dependent Variable: y				

Source: Author's Analysis

Table 6: Regression Negative emotions (y) and Feelings & Experience (x_1) and Time Spent (x_2) ANOVA

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	142.010	1	142.010	14.753	.000[b]
	Residual	981.836	102	9.626		
	Total	1123.846	103			
2	Regression	179.632	2	89.816	9.607	.000[c]
	Residual	944.214	101	9.349		
	Total	1123.846	103			
a. Dependent Variable: y						
b. Predictors: (Constant), x1						
c. Predictors: (Constant), x1, x2						

Source: Author's Analysis

The fitted model is given as follows:

$Y = a + b_1x_1 + b_2x_2$ --- (2)

or

Negative feelings (worry, depression and anxiety) = 6.567 + 0.306 feelings + 0.254 time spent

The estimated regression line indicates that emotional imbalance characterised by negative feelings such as worry, depression and anxiety is affected by two factors namely 'feelings' experience while using social media and 'time spent' on social media.

Both these factors significantly impact the emotional imbalance of a person as *t* value 3.71 (p = 0.000) and 2.006 (p = 0.048) (Table 7) corresponding to the estimated regression coefficients for the two factors respectively is significant i.e. its *p* value is less than 0.05 for both the factors.

As the estimated regression coefficients for the remaining three factors, namely obsession, other activities and stress buster are insignificant, they are excluded from the model while running a step-wise regression.

Table 7: Regression Negative emotions (y) and Feelings & Experience (x_1) and Time Spent (x_2) Coefficients

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	9.207	0.919		10.015	0.000		
	x1	0.320	0.083	0.355	3.841	0.000	1.000	1.000
2	(Constant)	6.567	1.598		4.111	0.000		
	x1	0.306	0.082	0.340	3.710	0.000	0.993	1.007
	x2	0.254	0.127	0.184	2.006	0.048	0.993	1.007

Excluded Variables[a]								
Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	x2	.184[b]	2.006	0.048	0.196	0.993	1.007	0.993
	x3	.056[b]	0.590	0.557	0.059	0.968	1.033	0.968
	x4	.040[b]	0.431	0.667	0.043	0.993	1.007	0.993
	x5	.074[b]	0.791	0.431	0.078	0.978	1.022	0.978
2	x3	.013[c]	0.141	0.888	0.014	0.916	1.091	0.916
	x4	.046[c]	0.499	0.619	0.050	0.992	1.008	0.986
	x5	.024[c]	0.244	0.808	0.024	0.900	1.112	0.900
a. Dependent Variable: y								
b. Predictors in the Model: (Constant), x1								
c. Predictors in the Model: (Constant), x1, x2								

Source: Author's Analysis

Table 7 depicts the beta coefficient of Feelings and Expression is 0.306, indicating that for every one-unit increase in Feelings and Expression while using social media, the negative feelings will increase by 0.306 units. The beta coefficient of Time Spent is 0.254, indicating that for every one-unit increase in Time Spent on social, the negative feelings will increase by 0.254 units. The standardized beta coefficients for Feelings and Expression while using social media is greater than Time Spent, indicating that Feelings and Expression have greater impact on negative feelings of an individual.

Segmentation of Respondents

Further, to group the respondents based on the factors of social media usage, cluster analysis is attempted. To determine the degree of similarity in the respondents on the basis of five important factors of usage of social media, the most suitable technique is cluster analysis. Cluster analysis is a group of multivariate techniques whose primary purpose is to group objects based on the characteristics they possess. Cluster analysis classifies objects (respondents, products, or other entities) so that each object is similar to others in the cluster based on a set of selected characteristics. The resulting clusters of objects then exhibit high internal (within-cluster) homogeneity and high external (between-cluster) heterogeneity. If the classification is done successfully, then the objects within the cluster are close together when plotted geometrically, and different clusters are far apart. Unlike other multivariate techniques, cluster analysis technique does not estimate the variate empirically but instead, the variable specified is used for the analysis. Basically, cluster analysis compares objects based on the variate and it does not estimate the variate itself.

Hierarchical cluster Analysis

For the purpose of analysis of the current study, hierarchical clustering procedure is applied to identify the number of clusters to stop at, and further, the number of clusters is taken as an input to finally identify the segmentation of respondents with a more fine-tuned cluster segmentation using *k* mean (non-hierarchical) cluster analysis. Ward's method (Hair *et al.,* 2018), the frequently used agglomerative techniques in hierarchical cluster analysis, is used in the analysis for making clusters of respondents based on the factors of social media usage. The inputs to these methods are distances (similarities) between pairs of clusters. Further, the clusters are validated using external variables.

The five factors so emerged were converted to summated scale, which are subsequently used in cluster analysis (CA) to establish clusters of respondents. The respondents are thus classified on the basis of homogeneity in the summated scale related to dimensions of social media usage patterns. Multicollinearity can be an issue in using cluster analysis. To resolve the problem of multicollinearity, it was decided to use the summated scale of the emerged factors as cluster variables that are not strongly correlated to another.

To decide the number of clusters to stop at, the most common approach was used, which is to observe the clustering process and note when the stress of bringing two clusters together becomes particularly large. Experience also indicates that it is rare to find a statistically significant solution with more than seven clusters **(Saunders, 1994)**. Cluster Solution using Ward's Method is an approach designed to minimize within cluster variance and examine what would happen if individuals joined a cluster. This approach tends to produce robust, dense, spherical clusters with distinct characteristics (**Everitt 1980**).

At the initial stage, the outliers are detected as cluster analysis which is sensitive to the inclusion of irrelevant variables as well as to outliers. To detect the outliers, graphical approach called profile diagram, listing variables along horizontal axis and the variable values along the vertical axis is used (Figure 3). From the graph, the peak points for the first factor 'feelings' is identified as a likely outlier corresponding to respondent ids 19, 53, 26 and 24. It is further confirmed using empirical approach and agglomeration schedule where these variables are merging with other cluster members at a later stage, even beyond 64 stage.

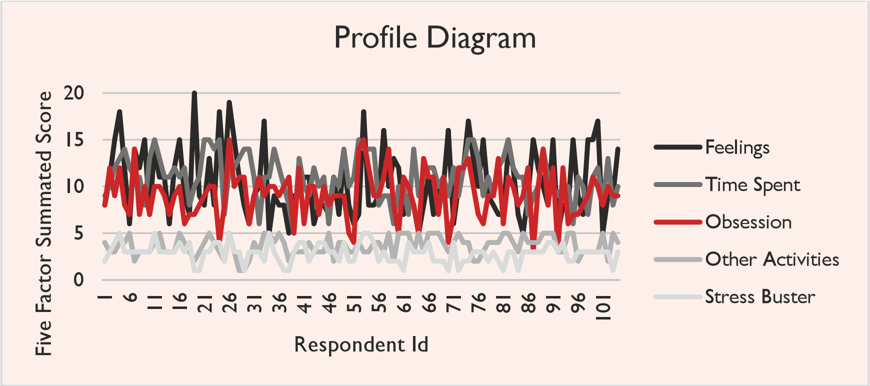


Figure 3: Profile Diagram

After the omission of the outliers, in an attempt to identify the number of clusters to stop at, the agglomeration coefficient is particularly used to identify the stopping rule. The highest percentage change is 19.034% (other than two cluster solution); hence, three cluster solution is identified (Table 5 Appendix and Figure 4).

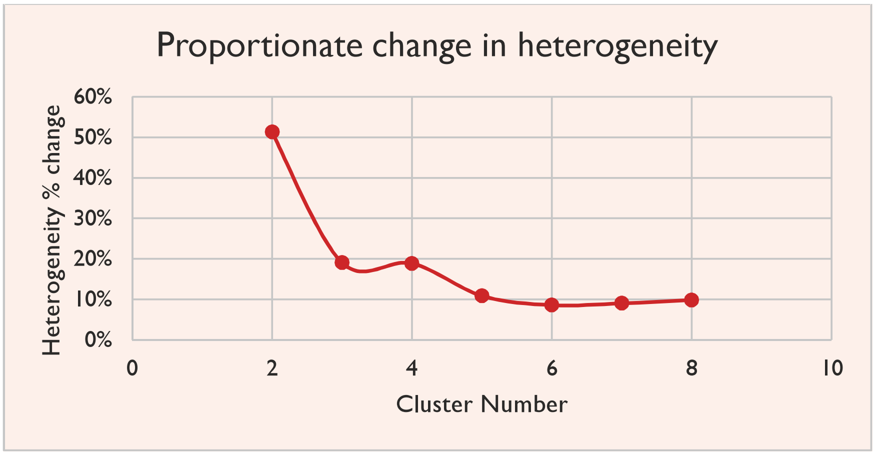


Figure 4: Plot of proportionate change in heterogeneity

After running hierarchical cluster, the membership is noted which shows each case being divided into a specific cluster number. The distinctiveness and significance of the cluster membership is examined using one-way ANOVA to confirm the differences between clusters in light of the research question and to define characteristics of the clusters.

No cluster contains less than 10% of observations; hence, all the clusters are retained and this primary assessment is sufficiently favourable to indicate moving on to non-hierarchical clustering. The cluster sizes are likely to change in the non-hierarchical analysis and observations will be reassigned. As a result, the final meanings of the three clusters will be determined in the non-hierarchical analysis. To fine-tune the distribution of the observations among the clusters, non-hierarchical cluster analysis (K-mean cluster) in SPSS ver. 20 is executed.

Non-Hierarchical Cluster Analysis (K- Mean Cluster Analysis)

There are two notable differences between hierarchical and non-hierarchical results. Cluster sizes: more even dispersion of observations among the clusters and resulted in cluster sizes of 15, 58, and 27 as compared to clusters of 29, 36 and 35 in the hierarchical analysis. Significance of clustering variable differences: delineate clusters that are usually more distinctive in variable means across three clusters. Four of the five cluster variates have very large F-values (Feelings, Time Spent, Obsession and Stress Buster). Hence, it adequately discriminates observations, with the exception of Other Activities.

Table 8 shows the non-hierarchical three-cluster solution which is a fine-tuned version of hierarchical cluster analysis. Following cluster assignment, clusters were verified and analysed with ANOVA, and descriptive statistics (**Bohorquez *et al.* 2019**). Following the similar method in the present study, the results of ANOVA are presented in Table 8. The *F*-statistic is significant at 1% level of significance for all the five factors of Social Media Usage except for the factor 'Other Activities'.

The Mean-Cantered Values give a clearer description of the distinction of the three clusters. All three clusters exhibit somewhat distinctive characteristics as discussed further.

Table 8: Profile of Three Clusters from Non-Hierarchical Cluster Analysis

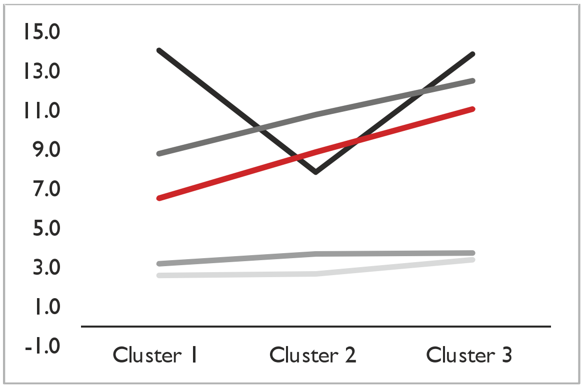
Factor of Social Media Usage	Mean Values for Cluster Number			Mean cluster var.	Mean-Cantered Values for Cluster Number			*F*-statistics	*p* value
	Cluster 1	Cluster 2	Cluster 3		Cluster 1	Cluster 2	Cluster 3		
Feelings	14.1	7.9	13.9	11.9	2.13	-4.08	1.95	105.8	**.00**
Time Spent	8.8	10.8	12.5	10.7	-1.90	0.09	1.81	15.2	**.00**
Obsession	6.5	8.9	11.1	8.8	-2.30	0.05	2.25	21.9	**.00**
Other Activities	3.2	3.7	3.7	3.5	-0.35	0.16	0.19	1.6	.21
Stress Buster	2.6	2.7	3.4	2.9	-0.30	-0.21	0.51	6.2	**.00**
N	15.00	58.00	27.00		15.00	58.00	27.00		

Source: Author's Calculation

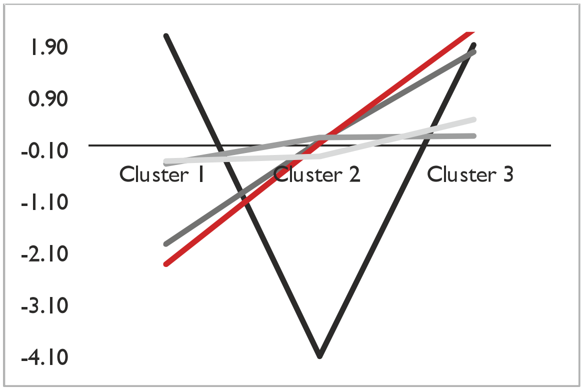
Cluster 1 (Sensitive): contains 15 observations and is best characterized by two factors: a very low mean on the factor 'Obsession' and highest score on 'Feelings'. This group of respondents are sensitive and feel down, depressed, irritable or hopeless over the internet. They often experience feelings of sadness and feel isolated as a result of using social media. They, on an average, are diagnosed with depression due to excessive use of social media. This category of respondents often get upset by people's reaction to their posts.

Cluster 2 (Balanced Emotions): contains 58 observations; most respondents are clubbed together in this cluster. They have a relatively lowest mean on 'Feelings'. This indicates that this group of respondents do not feel down, depressed or irritated by the use of social media. They are balanced in feelings and emotions and do not get carried away. This group of respondents are moderate in terms of spending time on social media usage. They are not at all obsessed in terms of feeling proud of using social media or getting upset on social media shutdowns.

Cluster 3 (Fanatical Emotions) contains 27 observations and has the highest score on 'Obsession' and 'Stress Buster'. This group of people get upset on social media shutdowns, feel proud about using social media and are logged in on most of the social media sites on mobiles and computer devices.



Graph 5: Mean Value for Cluster number (Non-hierarchical)



Graph 6: Mean-Centred Values for Cluster Number (Non-Hierarchical)

Cluster Stability

Sorting observations on a different variable, say age, and then performing the cluster analysis once again (with new seed point selected by the software), following the clustering routine, a cross-classification is performed. To analyse how stable is the cluster formed, a crosstab is created (Table 9). The cluster solution is very stable because the solution is produced with less than 10% of observations, being assigned to a different cluster (Hair *et al.*, 2018).

Table 9: Cross-Classification to Assess Cluster Stability

Count					
		Cluster Number from Second K-Means			Total
		1	2	3	
Cluster Number from First K-Means	1	1	0	14	15
	2	58	0	0	58
	3	0	26	1	27
Total		59	26	15	100

Source: Author's Analysis

The final task is to profile the clusters on a set of additional variables not included in the clustering variate or used to assess predictive validity. In this case, two characteristics are available - Age and Occupation - both are non-metric. Thus, cross-classification is used to test the relationship between the cluster and age, and occupation and cluster. Table 10 shows the crosstab between cluster and age, and cluster and occupation along with the chi-square statistic and p-value. The chi-square statistic is significant at 10% and 1% level of significance respectively for Age vs Cluster and Occupation vs Cluster. This indicates that the null hypothesis: the two attributes 'cluster' and 'age' are independent of each other is rejected at 10% level of significance. The null hypothesis: the two attributes 'cluster' and 'occupation' are independent of each other is rejected at 1% level of significance. Hence, significant χ^2 values are observed for both the profile variables. From Table 10, it is visible that cluster two characterised by balanced emotions comprises mainly of students in the age group of 18 to 25 years. It is also observed that there is no adult professional included in cluster one as characterised by sensitive or bothered by feeling down, depressed, irritable or hopeless over the internet. There are mostly students of the age group 18 to 25 years who show fanatical emotions included in cluster three.

Table 10: Profiling the Final Cluster Solution

Crosstab							
Count							
		Cluster Number of Case			Total	Chi-square	Sig (*p*-value)
		1	2	3			
Age	Below 20	3	19	10	32	11.74	0.068
	21-25	9	28	16	53		
	26-30	0	8	1	9		
	Above 30	3	3	0	6		
Total		15	58	27	100		
Occupation	Student	9	40	22	71	24.248	0.00
	Other professionals	6	18	5	29		
Total		15	58	27	100		

Source: Author's Analysis

Conclusion

The key objective of this study was to identify the impact of social media usage on individuals' behaviour. This included negative emotions such as worry, depression and anxiety. Finally, individuals were categorised based on factors of emotional imbalance revealed by the study. A comprehensive review of literature was conducted and multivariate cross-sectional data was analysed using supervised and unsupervised algorithm. Various aspects of the psychological changes in an individual due to Social Media usage was studied. It can be concluded that there are five important factors an individual experiences while using Social Media - Feelings, Time Spent, Obsession, Other activities and Stress Buster. The nomenclature of factors is done with reference to usage of Social Media. Further, these factors of usage of social media were considered as independent variables and negative feelings (worry, depression and anxiety) individual experiences in life were taken as dependent variables while running a multiple regression model. Stepwise multiple regression resulted in a model where feelings and time spent, two prominent factors with reference to social media usage, majorly proved statistically significant in affecting negative feelings or emotional imbalance of an individual. The factors were also used to identify different segments of respondents using cluster analysis. The clusters of respondents were named as Sensitive, Balanced Emotions and Fanatical Emotions. The cluster analysis was successful in performing segmentation of the individuals into three emotional expression-based groups while using social media. The process not only created homogenous groupings of customers based on their predictions, but also found that these clusters met the tests of predictive validity and distinctiveness on additional sets of variables, age and occupation, which are necessary for achieving practical significance. It can finally be concluded that there are different perspectives of Social Media usage for an individual, with varied emotional expression.

Managerial Inferences

The empirical work conducted in the present study contributes to the existing literature on social media usage and its factors affecting emotional imbalance of an individual. The findings of the study have important inferences from the viewpoint of managers. The foremost concern the results communicate is the importance of having a mix of factors affecting social network. The first factor is related to Feelings, an expression that shows the way an individual feels about social media. Their experience, reaction on a post, depression due to excessive use, irritation, etc. lead to emotional imbalance of an individual. A study done by **Pantic *et al.* (2012)** using high school students as the sample set found that there was a statistically significant positive correlation between depressive symptoms and time spent on social networking sites. **Pantic (2014)** found that there might be a possibility that different age groups (i.e., high school children vs. older adolescents) react differently to social networking sites' content and challenges.

The second factor is Time Spent which shows the amount of time spent, number of visits and preference of an individual on social media. It is likely that as the time spent on the internet and social media increases, it may influence an individual's thoughts, emotions and behaviour. To examine the impact of the five factors, namely, feelings, time spent, obsession, other activity engagement and stress buster on the emotional expression of an individual while using social media, multiple regression was run using stepwise method. The results indicated that emotional imbalance i.e. having negative feelings such as worry, depression and anxiety were significantly affected by two factors of usage of social media, namely, feelings developed as a reaction to the usage of social media and time spent on the social media. The regression result was in line with the study done by **Kraut *et al.* (1998)**, one of the first studies to indicate internet being used in common, significantly touches social relationships and involvement in community life. The study found that increased time spent online was interrelated to a weakening in communication with family members, as well as a drop in the internet user's social circle, which might further lead to increased emotional state of depression and loneliness. This work was followed by numerous other studies where it was advocated that computer use might have adverse effects on children's social involvement **(Subrahmanyam *et al.*, 2000)**. Even though social networks facilitated an individual to interact with a huge number of people, these interactions were mostly superficial and cannot sufficiently supplant everyday face-to-face communication **(Pantic *et al.*, 2014)**.

The third factor, obsession, includes the effects of social media on the individual. Obsession implies prolonged use of social media sites, which results in the individual disregarding offline social activity with his family and offline friends. In addition, **Pantic *et al*. (2014)** have observed that sudden interruption of online social networking (i.e., lack of Internet connection), in some chronic users, might cause signs and symptoms that at least partially resemble the ones seen during drug/alcohol/nicotine abstinence syndrome. The obsession for social networking sites has become a potential addiction disorder which has so far been discussed by many researchers (**La Barbera et al., 2009; Kuss DJ, 2011; Echeburua and de Corral, 2010; Griffiths, 2012; Andreassen et al., 2012**). Obsession for social networking sites in a way directly results in irrational procrastination as studied by **Shuai-lei (2018)**. The researchers identified that social networking sites result in fatigue that acted as a mediator in the relationship between addiction for social networking and irrational procrastination. According to Davis' cognitive–behavioural theory **(Davis, 2001)**, those who experience social networking addiction are likely to spend more time and cognitive resources on social networks. This results in increasing negligence of offline professional, social, and personal responsibilities, which, in turn, results in negative and irrational procrastination. Addiction to social media platforms can also affect the business environment in certain conditions as studied and reviewed by **FUCIU (2019)**.

The fourth factor 'Other Activity Engagement' revealed how frequently an individual played outdoor games or engaged in mind related activities other than using social media. These activities help relax and refresh the mind of an individual. And the fifth factor was 'Stress Buster' which shows the frequency of the effect of social media for reducing stress experienced by an individual.

It has become increasingly important to identify the ways schools, youth organizations and parents make efforts to improve the social network of their children. Parents have a significant impact on the friendships built by their children **(Dickson *et al.*, 2018)**. It is recommended that parents use an open-door policy for their children's friends. The policy will allow their children to invite their friends home to socialize. The teachers of schools may monitor children and identify those who have very few friends. Teachers may possibly initiate a program which will help these children to mix in the group. Besides, teachers themselves could become an important source of social conservation.

Limitations of the Research

The results of the study can be applied keeping in mind the following limitations. Data was collected from a sample set of 104 individuals whose experiences and behaviours may change over time. The study is based on the effects of social media in its present form, which is changing dynamically due to introduction of new technology. The present study uses a structured questionnaire based on past literature considering emotional experiences a social media user may undergo based on the factors of social media use in terms of how he feels or how much time he spends and whether he considers usage of social media as a source of relieving stress. There might be other factors, which may correlate with other aspects of behaviour and psychology of an individual while using social media that have not been covered in this study. A deep dive, particularly considering any specific aspect of the human psychology may be considered to examine the effects. The present study considers only age and profession as demographic factors; there might be other demographic variables which might play an important role in studying social media use and its effects. Other aspects of social media usage may be studied, particularly video games and their impact on teenagers and the youth, which may lead to short-term and long-term physiological effects as well as aggressive thoughts.

An important limitation of the present study is the use of a cross-sectional design, which does not allow making any certain assertion about the interconnection of the relationships under study. This would require the use of longitudinal or experimental research. Another concern is the possibility that selection biases may have been at work with respect to the specific respondents that took part in filling the questionnaire.

Implications for Future Research

The findings of the present study indicate that individuals are very active on Social Media. Perfect analyses of the psychology of an individual while on Social Media is a critical subject matter. It will help companies to easily target their audience and sell specific kinds of products or services required by an individual. However, from the point of view of an individual, constantly being updated on social media, while possibly being a stress buster, may result in mental and physical illnesses, and emotional imbalance in the long term.

From the viewpoint of research, it offers adequate scope to undertake further research in a related field of study. Instead of just focusing on the negative effects of social media, one could definitely look into the positive aspects of it. This will enable a researcher to study the topic holistically. The study could also take into consideration analysis of individuals' behaviour on social media platforms that will provide insights to companies trying to sell their products or services online. The study is useful for the individual as well as for companies. There is also a need for additional research to consider potential factors such as social networking site fatigue **(Shuai-lei, 2018)** and sleep quality **(Xanidis and Brignell, 2016)**, and moderators such as effortful control and mindfulness **(Shuai-lei, 2018)**. Studies may also be carried out to identify more plausible arguments about how (or why) and when social networking addiction leads to neglecting other responsibilities.

The association between social media use and mental health or psychological behaviour is likely to be mediated and/or moderated by, say, measures of school atmosphere or neighbourhood or working environment. This association could be one possible hypothesis which could be tested empirically. Additionally, similar to the study conducted by **Bruggeman *et al.* (2019)** future research could cover the impact of social media on a multitude of variables that the present study did not address, namely, the child's performance in school, functions of the neural system, and body mass index (BMI).

There are several systematic reviews addressing usage of Internet by adolescents and health stress with the top priority to move from correlational to causal analysis **(Best *et al.*, 2014; Pantic, 2014; Strasburger *et al.*, 2010)**, which indicates that studies are carried out beyond cross-sectional to longitudinal data collection. That there is 'a lack of confirmation testing the explicit course of the association between social media technology and wellbeing' **(Best *et al.*, 2014)** primarily has to do with data limitations. The prominence of wellbeing effects of online media on children and the youth cannot be exaggerated. Regardless of the challenges involved, additional studies with better quality information and measurements are noticeably necessary.

Applicability and Generalizability

The study could be applicable to social media users across a wide cross section of demographics. This conclusion is arrived at because the segmentation of social media users in three clusters is based on the five factors that emerged, namely, feelings, time spent, obsession, other activity engagement and stress buster. The results of cluster analysis follow all the assumptions and has also followed all the validation rules. The primary data collected in the research represented respondents who were majorly either students or working professionals. As reported earlier, they belong to the age group of 18 to 35 years with the mean age of 28 years of which most of the respondents used social media very often in a day. The study has been conducted mostly in some of the Tier II towns and metro cities of Mumbai and Delhi. However, the findings of these studies are certainly applicable to respondents with similar demographic profiles in terms of age, education level and usage of social media, in any part of the country. The researcher has observed that there are five important factors of social media usage, namely, feelings, time spent, obsession, other activity engagement and stress buster. The study also revealed a significant impact of two factors of usage of social media, namely, feelings developed as a reaction to the usage of social media and time spent on the social media resulting in negative emotions such as worry, depression and anxiety which ultimately creates emotional imbalance. The users are mainly categorised in three segments based on their emotional expression while using social media namely Sensitive, Balanced Emotions and Fanatical Emotions. The responses can therefore be considered to be generalizable across regions.

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Appendix

Table 1: Cronbach's Alpha if Item Deleted

	Cronbach's Alpha if Item Deleted
How often do you visit social media?	.696
How often do you spend your time on social media?	.678
How often do you prefer having conversation on soc ial media?	.685
How often have you ever experienced feelings of sadness as a result of using social media?	.682
How often do you get upset by people's reaction to your post?	.674
Have you ever been diagnosed with depression due to excessive use of socia l media?	.699
Have you ever experienced feelings of isolation as a result of social media?	.682
How frequently does social media reduce your stress?	.690
How often have you been bothered by feeling down, depressed, irritable or hopeless over the internet?	.690
How often do you prefer playing outdoor games or mind related activities?	.710
How many friends do you have in real life whom you can actually discuss your problems with?	.711
How often do you prefer discussing your problems or issues with your family or friends?	.700
Does worry or anxiety interfere with your sleep or ability to concentrate?	.683
Have you been bothered by feeling tired or having little energy?	.673
Do you experience intense anxiety or worry and find it difficult to control?	.680
Approximately how many total Facebook friends do you have?	.710
In the past week, on average, approximately how much time PER DAY have you spent actively using Social Media?	.687
Would you be upset if any Social Media shuts down?	.679
Do you feel proud telling people that you are using social media?	.685
Your Facebook, Instagram and Snapchat always logged in your mobile, computer and other devices?	.698

Table 2: Assessing the appropriateness of factor analysis for given variables: Measures of Sampling Adequacy and Partial Correlations among variables

		Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q22	Q23	Q24	Confidence at 1% significance level
Reproduced Correlation	Q5	.746[a]	0.8	0.4	0.2	0.1	-0.3	-0.1	0.2	-0.2	-0.2	0.1	0.0	0.1	
	Q6	0.8	.814[a]	0.5	0.3	0.2	-0.2	0.1	0.2	-0.1	-0.2	0.2	0.2	0.2	
	Q7	0.4	0.5	.635[a]	0.1	0.2	-0.2	0.2	0.4	0.0	0.3	0.2	0.3	-0.1	
	Q8	0.2	0.3	0.1	.728[a]	0.4	0.2	0.5	-0.1	0.5	-0.1	0.1	-0.1	0.2	
	Q9	0.1	0.2	0.2	0.4	.452[a]	0.3	0.4	0.3	0.4	-0.1	0.4	0.3	0.1	
	Q10	-0.3	-0.2	-0.2	0.2	0.3	.659[a]	0.3	0.2	0.4	-0.3	0.1	0.0	-0.1	
	Q11	-0.1	0.1	0.2	0.5	0.4	0.3	.578[a]	0.2	0.5	0.1	0.1	0.1	-0.1	
	Q12	0.2	0.2	0.4	-0.1	0.3	0.2	0.2	.631[a]	0.0	-0.1	0.3	0.3	-0.2	
	Q13	-0.2	-0.1	0.0	0.5	0.4	0.4	0.5	0.0	.569[a]	0.0	0.1	0.0	0.0	
	Q14	-0.2	-0.2	0.3	-0.1	-0.1	-0.3	0.1	-0.1	0.0	.811[a]	0.0	0.2	0.0	
	Q22	0.1	0.2	0.2	0.1	0.4	0.1	0.1	0.3	0.1	0.0	.632[a]	0.6	0.4	
	Q23	0.0	0.2	0.3	-0.1	0.3	0.0	0.1	0.3	0.0	0.2	0.6	.701[a]	0.4	
	Q24	0.1	0.2	-0.1	0.2	0.1	-0.1	-0.1	-0.2	0.0	0.0	0.4	0.4	.639[a]	
Residual[b]	Q5		-0.1	-0.1	-0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	1
	Q6	-0.1		0.0	0.0	-0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3
	Q7	-0.1	0.0		0.0	-0.1	0.1	-0.1	-0.2	0.0	-0.1	-0.1	0.1	0.1	1
	Q8	-0.1	0.0	0.0		-0.1	0.0	-0.2	0.0	-0.1	0.0	0.0	0.1	-0.1	1
	Q9	0.1	-0.1	-0.1	-0.1		0.0	-0.1	-0.1	-0.2	0.1	-0.1	0.0	0.0	0
	Q10	0.0	0.1	0.1	0.0	0.0		-0.1	-0.1	-0.2	0.1	-0.1	0.0	0.1	0
	Q11	0.0	0.0	-0.1	-0.2	-0.1	-0.1		0.0	-0.1	-0.1	0.0	-0.1	0.1	1
	Q12	0.0	0.0	-0.2	0.0	-0.1	-0.1	0.0		0.0	0.1	-0.1	-0.2	0.2	1
	Q13	0.0	0.0	0.0	-0.1	-0.2	-0.2	-0.1	0.0		-0.1	0.1	0.0	0.0	2
	Q14	0.1	0.0	-0.1	0.0	0.1	0.1	-0.1	0.1	-0.1		0.0	-0.1	0.0	1
	Q22	0.0	0.0	-0.1	0.0	-0.1	-0.1	0.0	-0.1	0.1	0.0		-0.1	-0.2	1
	Q23	0.0	0.0	0.1	0.1	0.0	0.0	-0.1	-0.2	0.0	-0.1	-0.1		-0.2	1
	Q24	0.0	0.0	0.1	-0.1	0.0	0.1	0.1	0.2	0.0	0.0	-0.2	-0.2		0
Extraction Method: Principal Component Analysis.															13
a. Reproduced communalities															52%
b. Residuals are computed between observed and reproduced correlations. There are 45 (57.0%) nonredundant residuals with absolute values greater than 0.05.															

Table 3: Eigenvalues and Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.788	21.449	21.449	2.788	21.449	21.449	2.140	16.461	16.461
2	2.072	15.939	37.388	2.072	15.939	37.388	2.134	16.416	32.877
3	1.500	11.538	48.926	1.500	11.538	48.926	1.867	14.358	47.235
4	1.156	8.891	57.817	1.156	8.891	57.817	1.252	9.633	56.868
5	1.079	8.304	66.120	1.079	8.304	66.120	1.203	9.252	66.120
6	.855	6.577	72.697						
7	.808	6.217	78.915						
8	.704	5.418	84.333						
9	.546	4.204	88.537						
10	.503	3.869	92.406						
11	.388	2.986	95.392						
12	.348	2.678	98.070						
13	.251	1.930	100.000						
Extraction Method: Principal Component Analysis.									

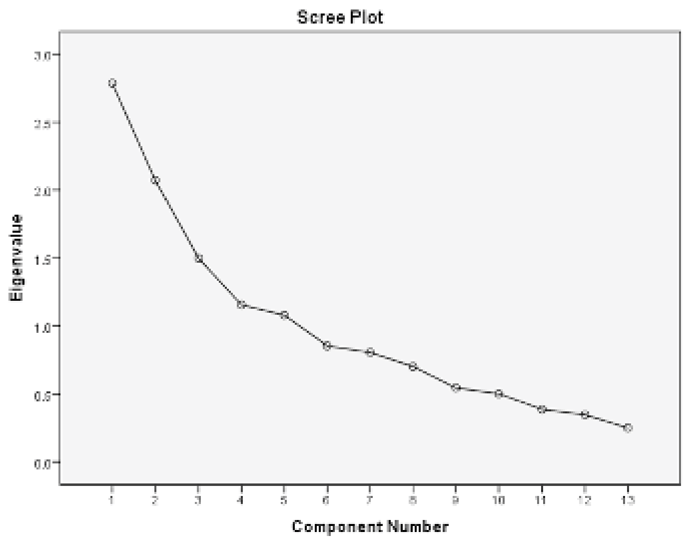
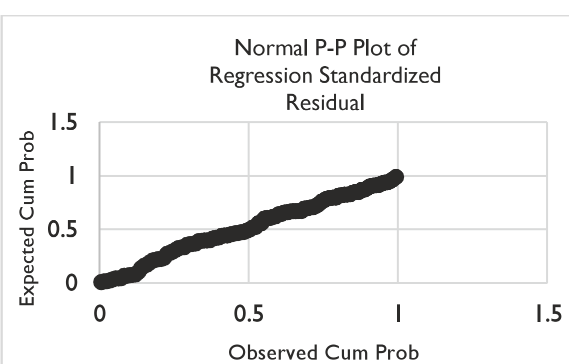


Figure 1: Scree Plot

Table 4: Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
How often have you been bothered by feeling down, depressed, irritable or hopeless over the internet?	.736				
How often have you ever experienced feelings of sadness as a result of using social media?	.730				
Have you ever experienced feelings of isolation as a result of social media?	.722				
Have you ever been diagnosed with depression due to excessive use of social media?	.499			-.482	
How often do you get upset by people's reaction to your post?	.497				
How often do you spend your time on social media?		.880			
How often do you visit social media?		.854			
How often do you prefer having conversation on social media?		.494		.408	.424
Do you feel proud telling people that you are using social media?			.810		
Would you be upset if any Social Media shuts down?			.780		
How often do you prefer playing outdoor games or mind related activities?				.879	
How frequently does social media reduce your stress?					.702
Your Facebook, Instagram and Snapchat always logged in your mobile, computer and other devices?			.518		-.586
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.					
a. Rotation converged in 6 iterations.					



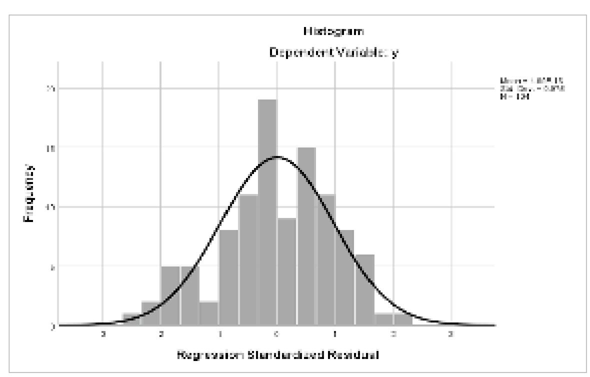


Figure 2: Residual following Normal Distribution

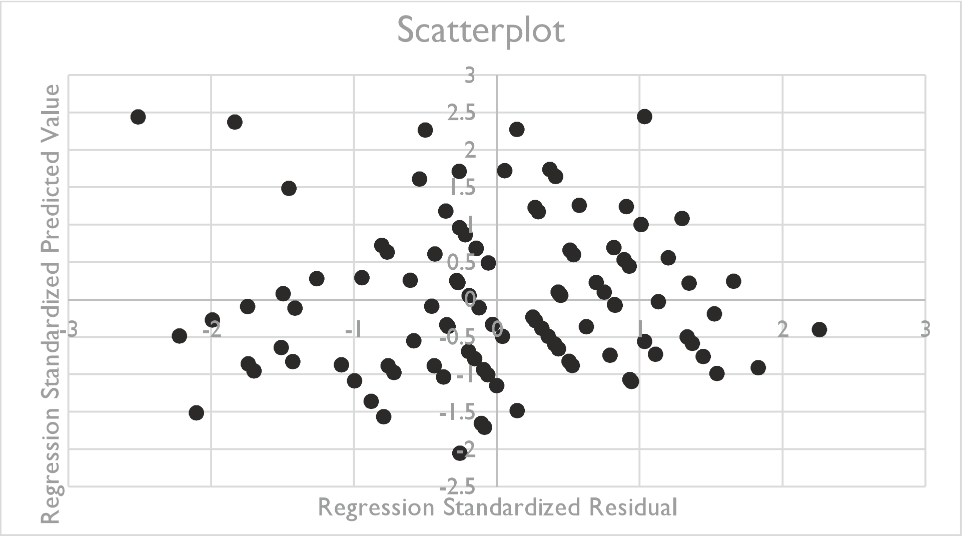


Figure 3: Scatterplot of Standard residual Vs Standard predicted value

Table 5: Stopping Rule for the Hierarchical Cluster Analysis

				Stopping Rule		
				Agglomeration Coefficient		
Stage	Cluster Combined		Cluster Number after combining	Coefficient Value	Differences	Proportionate change in heterogeneity
	Cluster 1	Cluster 2				
92	2	5	8	894.911	88.119	9.847%
93	4	23	7	983.030	88.699	9.023%
94	10	12	6	1071.729	91.818	8.567%
95	1	13	5	1163.547	126.424	10.865%
96	2	20	4	1289.971	243.417	18.870%
97	1	4	3	1533.388	291.864	19.034%
98	2	10	2	1825.252	935.858	51.273%
99	1	2	1	2761.110		

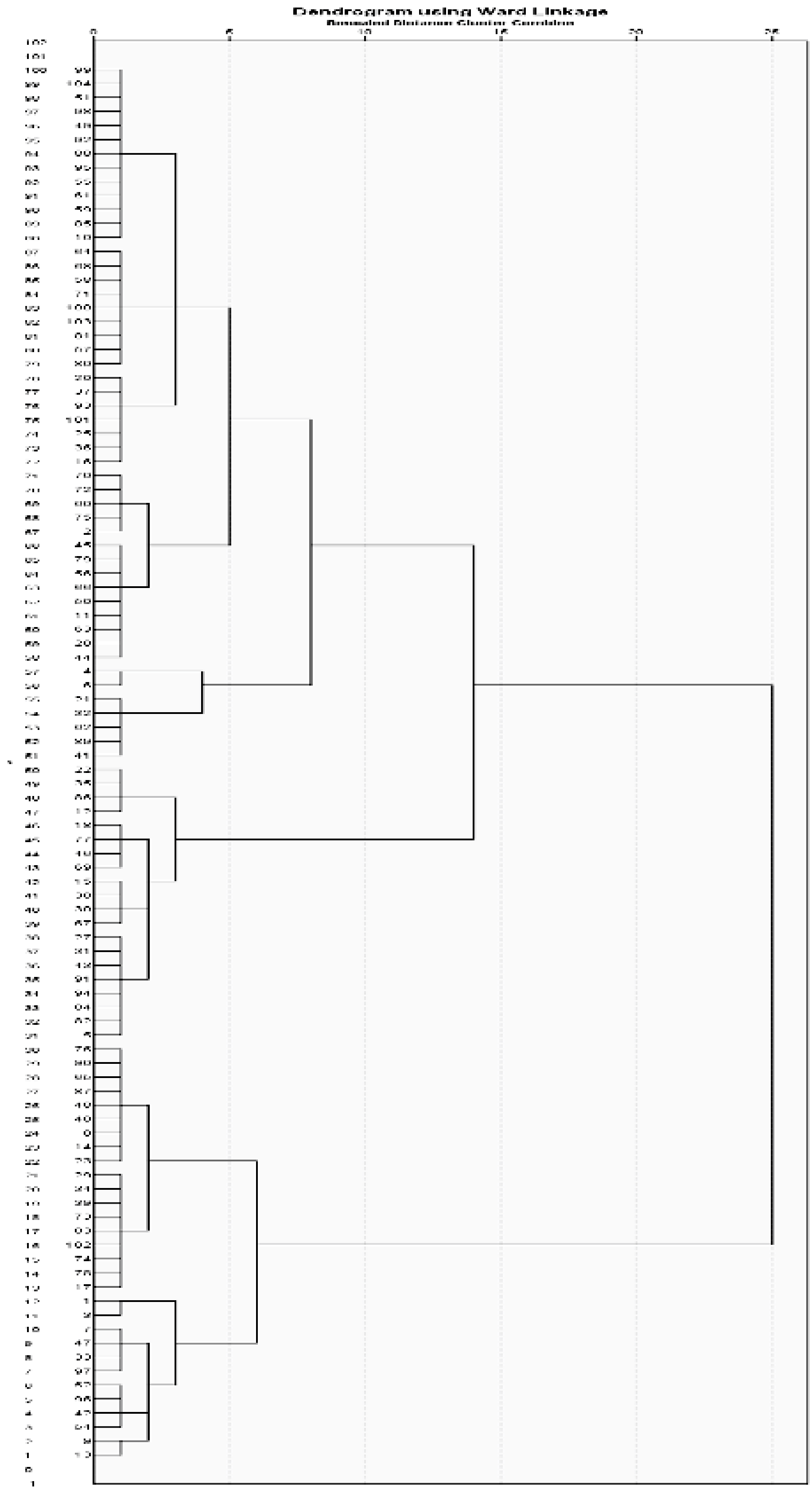


Figure 4: Dendogram (Hierarchical Cluster Analysis)