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THE ROLE OF EMOTIONAL INVESTMENT BETWEEN SOCIAL MEDIA USAGE AND LIFE SATISFACTION

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Abstract

The consumption of social media has grown ingrained in the lives of today's youth. The present study examined four possible explanations with various factors for the mixed findings on the association between social media use and well-being. A serial mediation models were proposed to examine the relationship between social media usage and life satisfaction through Emotional Investment (EI). The correlational and mediation method was adopted on data received from 660 Indian participants. The results revealed that the most critical factors influencing life satisfaction were passive social media usage as compared to the total time spent on social media (TTSSM), and active and active non-social usage (ANSU). Additionally, the present study revealed that EI is the root cause of poor life satisfaction. The present study's findings are strong enough to

encourage parents, educators, and health professionals to counsel young people about their EI in social media.

Keywords: social media; emotional investment, active, passive, active non-social, life satisfaction

Introduction

In the twenty-first century, the use of social platforms is a constantly increasing activity. Around 43% of users increase their time spent on social media (Chaffey, 2021). Worldwide, 4.20 billion (53.6%) users were active by January 2021 (Chaffey, 2021). In India, 448 million users were active on social media and 78 million (21%) users increased during 2020-2021 (Kemp, 2021). According to data obtained from the ad planning tools of the most popular social networking sites, at the beginning of 2023, there were 398.0 million users in India who were 18 years of age or older, or 40.2 percent of the total population of the nation (Kemp, 2023). In general, 67.5 percent of all internet users in India in January 2023 (regardless of age) used at least one social media platform (Kemp, 2023).

Studies on social media have shown mixed results as far as its impact is concerned. Some studies showed that individuals who spend more time on social media platforms were more tend to experience anxiety and depression symptoms (Banjanin et al., 2015). Excessive usage of social media has negative consequences for users' personal, professional, and/or social, lives (Griffiths et al., 2014). Multiple studies have revealed that excessive usage of social networking sites has positive correlations with stress, anxiety, and depression as well as negative correlations with academic performance, all of which have a detrimental impact on life satisfaction (Mamani-Benito et al., 2022, Hawi & Samaha, 2016). However, for the older age group, it was found that satisfaction from social media use activities positively associates with domain life satisfaction (Ractham et al., 2022). Due to the mixed findings of the studies, it becomes essential to investigate social media and its outcomes for better life satisfaction. However, to conclude that the consequences are due to the total time spent on social media (TTSSM) and the frequency of social media use is excessively simplistic.

Previous studies on social media usage and well-being focused on the frequency and duration of social media use. Considering the usage of social media by young adults, the frequency and duration of social media usage may not be enough to identify the underlying reason for diminishing well-being. According to studies (Burke et al., 2010), the two most prevalent social media usage styles are active and passive use. On social media, active use involves sharing content, liking it, posting comments on it, and interacting with others, whereas passive use is the act of merely browsing other people's posts or content shared by friends without liking, commenting, or participating (Verduyn et al., 2017). As a result, using social media actively versus passively elicits various emotional reactions. Therefore, it becomes essential to examine the types of usages (active vs passive) instead of only investigating the duration or frequency of social media.

Young adults deeply care the social media resulting in the induction of emotions while using social media, for instance, users feel disappointed and disconnected when they were not able to use social media (Woods & Scott, 2016) termed EI. As defined by Jenkins-Guarnieri et al. (2013), EI in social media use is the degree to which an individual gets angry when they are unable to use social media, feels detached when not signed in, and believes social media is crucial to maintaining relationships with others. As an individual increases the time spent on social media, the probability of involving emotionally also increases leading to certain life satisfaction. However, social media provided access to positive and inspirational information that might enhance mental health by connecting users with resources that increased their awareness of their own mental health.

It was also found that most of the studies conducted on social media were self-reported studies in which errors cannot be eliminated. Therefore, it is required to use technology to track the TTSSM and various social media platforms. Hence, the current study applied the Android application technology to track the respondent's TTSSM and various social media platforms on which the user spent their leisure time. Therefore, in light of these findings, we hypothesize that,

H1: TTSSM influence negatively to life satisfaction.

Concentrating only on the duration spent on social media may not help us to identify the prime cause of poor life satisfaction. Therefore, it will be important to include various other social media usage factors for example active-passive usage of social media. Gerson et.al. (2017) found that the uses of Facebook can be classified into three subscales: active social use, active non-social use (ANSU), and passive use. Users who are actively involved with social platforms, creating material, and chatting with friends are said to be active users. Using Facebook to build social capital (Ellison et al., 2007), call on friends for help (Liu & Yu, 2013), and create social connectedness (Grieve et al., 2013), all that has been related to a number of subjective well-being measures (Ellison et al., 2007). The second component is ANSU, in which only liking a post is considered (Gerson et.al. 2017). The presence of ANSU was surprising, as it denotes a type of SM interaction that is halfway between active and passive. The ANSU components indicate a degree of SM involvement in which a user approves the content posted by others by liking the post but does not interact directly with friends. Because of its non-social nature.

Individuals using social media actively express their feelings and emotions with others which helps in positive mental health, whereas passive usage results in feelings of envy and inferiority leading to negative mental health (Verduyn et al., 2017). Both active and passive social media use seems to be a factor causing emotional distress and connected to poor mental health leading to detrimental life satisfaction. It makes sense that being actively involved in social media usage improves one's social network, which could boost one's social network and feelings of connectedness, conversely, passive social media usage implies exposure to too positive images of others because people often promote themselves in overly attractive ways on social media. Most of the studies were conducted on active and passive usage of social media whereas, there is one grey usage also available between active and passive usage i.e., ANSU of social media which may impact life satisfaction. On basis of the aforementioned findings, we hypothesize that,

H2 (a): Active usage of social media will positively affect life satisfaction.
H2 (b): ANSU usage of social media will not affect life satisfaction.
H2 (c): Passive usage of social media will negatively affect life satisfaction.

Social Media and Emotional Investment (EI)

Social media creates unique social pressure on individuals to be available all the time to respond to the messages and like the content instantaneously (Thomée et al., 2010). A previous study found that "friends typically build emotional closeness links which are unsurpassed in individuals' social lives," and while people may find it difficult to express emotion within their family relationships, they “can often reduce their guard, when one or more cohorts are present (Gaines et al, 1998). A previous study found that higher EI is linked with depression and anxiety among university students (Alsunni & Latif, 2021). Very limited literature is available on the EI of social media users (Woods & Scott, 2016). Therefore, more studies are needed to examine the effect of the EI of social media users on life satisfaction. Studies reported the effect of social media usage on life satisfaction, still, more knowledge is needed to shed insights on which specific factors or combinations of factors involve impair, or are of no relevance to the well-being of social media users (Meier and Reinecke, 2020). Hence, it is worth investigating whether active, passive usage and most importantly non-active use can impact well-being through the EI of social media user.

Filling the gap arising out of the inconclusiveness of the extant studies regarding the identification of factors responsible for diminishing well-being, the current study contributes its bit to the coffers of the academic literature by proposing four serial mediation models (SMM1 to SMM4) in which EI used as a mediator to investigate the link between social media usage (TTSSM and active-passive usage) and well-being (life satisfaction). The current study proposed serial mediation models (SMM) with various factors for example SMM 1 (Figure 1) includes EI (M1) as mediators between social media usage (TTSSM) and life satisfaction,

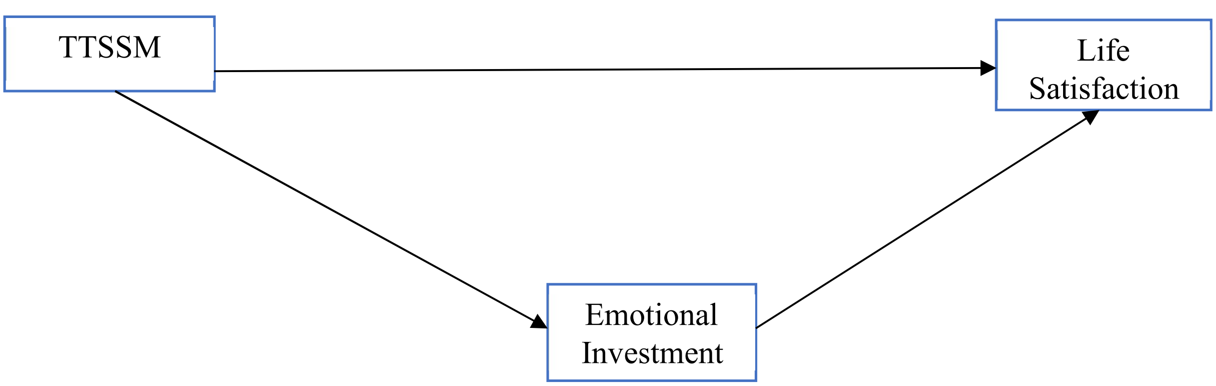

Figure 1: Serial Mediation Model 1 (SMM 1)

SMM2 (Figure 2) includes EI (M1) as mediators between active social media and life satisfaction,

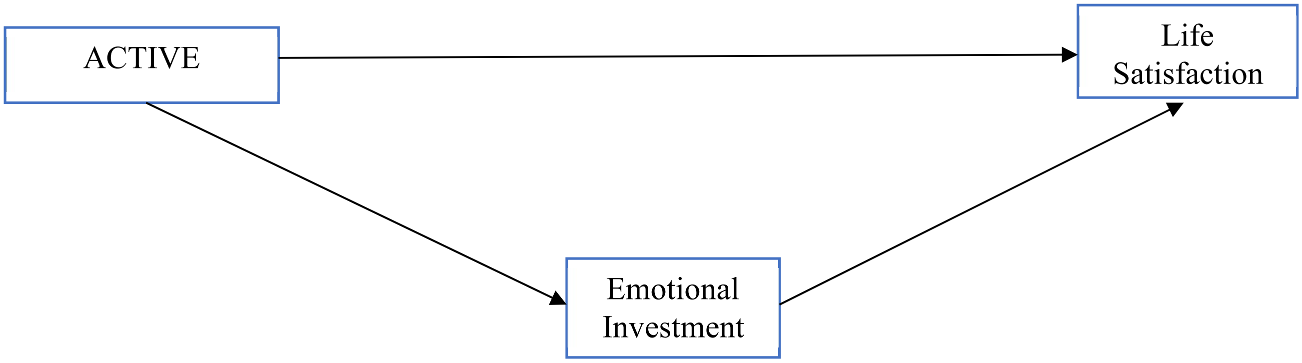

Figure 2: Serial Mediation Model 2 (SMM 2)

SMM 3 (Figure 3) includes EI (M1) and self-esteem (M2) as mediators between passive social media and life satisfaction and lastly,

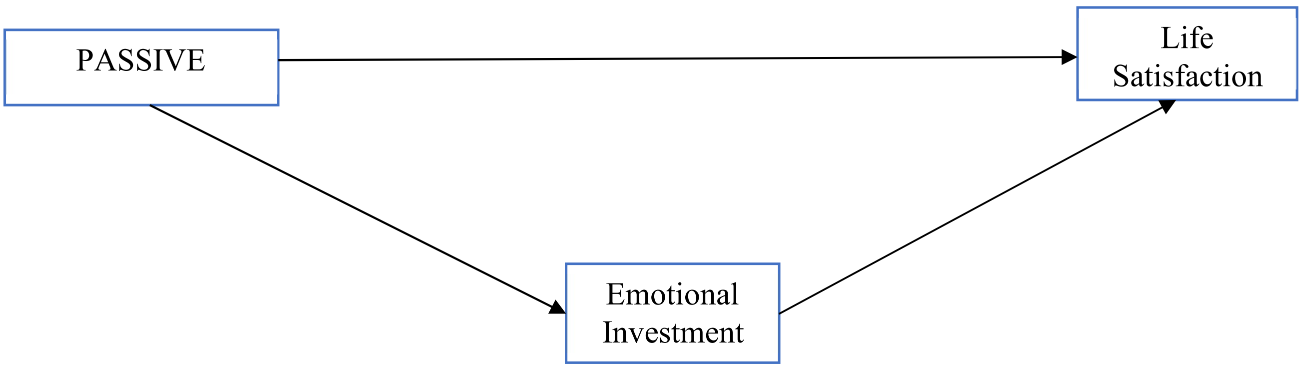

Figure 3: Serial Mediation Model 3 (SMM 3)

SMM 4 (Figure 4) includes EI (M1) and self-esteem (M2) as mediators between active non-social media and life satisfaction.

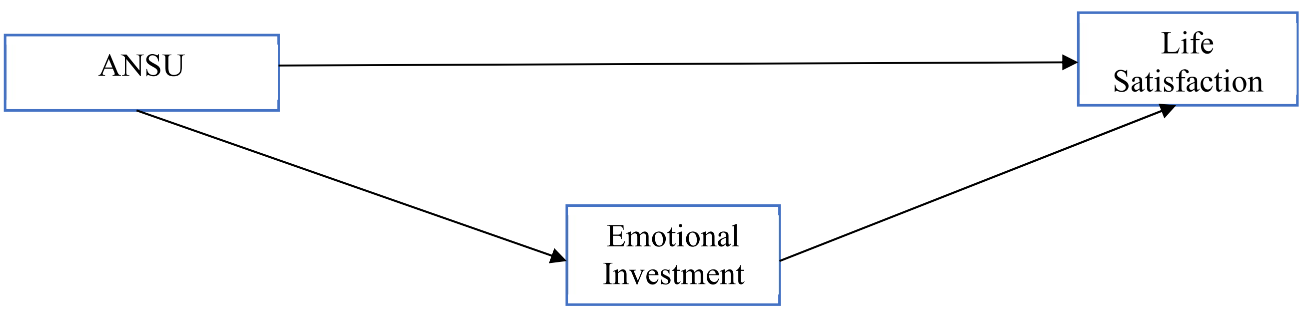

Figure 4: Serial Mediation Model 4 (SMM 4)

Therefore, on the basis of the above findings we hypothesized that;

H3 : EI do not mediate the relationship between TTSSM and life satisfaction.
H4 (a): EI do not mediate the relationship between active usage of social media and life satisfaction.
H4 (b): EI do not mediate the relationship between passive usage of social media and life satisfaction.
H4 (c): EI do not mediate the relationship between active non-social usage of social media and life satisfaction.

Methods

Participants, design, and procedure

The participants were selected through the snowball sampling method during the period of March 2022. The responses for the current study were collected from people aged 18 years onwards, due to survey started from the university students. The questionnaire comprised several questions that helped the researcher to determine the participant's eligibility to participate in the present study. The participant's selection was based on a few criteria, which were included in the screening questionnaire. Making use of the existing participants for getting newer ones in, the snowball sampling method was used as it is a non-probability referral chain-forming sampling method (Ghaljaie et al., 2017). The primary data was taken at the onset of the study and through the primary data; the respondents were encouraged to refer their friends, family, and acquaintances to take part in the study. The Snowball sampling technique is specifically used when the population is unknown. Recently few studies have used this method successfully to investigate different mental health issues in the population (Arafa et.al., 2021).
Initially, the students were contacted for participation in the survey. After receiving consent from the students, they have been encouraged to contact their interested friends, relatives, mentors, etc. as much as possible to participate in the study, henceforth the chain was created for the participants to take part in the study. To encourage the participants to take part in the study and spread the word among their acquaintances, they have been given non-monetary incentives for example online access to the university library, events etc. Keeping the participation voluntary, the respondents were anonymous and could withdraw at any point in time. Setting the context, the study objectives, and data confidentiality were explicitly taken care of by the university's ethical committee on the form's first page.

Subsequently, after receiving the consent form with a few eligibility questions and being selected for the study, participants were asked to install an Android application in their respective Android devices to track TTSSM. The participants were instructed to keep the Android app for at least fifteen days to track their social media usage. After seven days of usual social media usage, participants must submit the screenshots through the Google form (Figure 5).

Figure 5: Screenshot of Android application

Participants

The survey assessed 854 participants, among 854, 40 participants who were unhealthy from the chronic disease were excluded from further analysis. Out of these 814, 660 (81%) responded by completing the questionnaire and were considered for advanced statistical analyses. The sample consists of 52.1% male (n = 344) and 47.9% female (n = 316) (Table 1).

Factors	**N (%)**	**M (SD)**	**Min-Max**	**Reliability (α)**
Gender				
Male	344 (52.1)			
Female	316 (47.9)			
Age				
18-28 years	206 (31.2)			
28-38 years	190 (28.7)			
38-48 years	135 (20.4)			
48 -60 years	129 (19.5)			
Total Time spent on social media (TTSSM), hours		2.44 (0.82)	1-4	
Q1 (0-13)	90 (13.6)			
Q2 (13-26)	238 (36.1)			
Q3 (26-39)	282 (42.7)			
Q4 (39-52)	50 (7.6)			

Active-passive usage	660	23.07 (9.44)	00-52	0.913
Active usage	660	8.56 (4.57)	00-20	
ANSU	660	5.36 (3.29)	00-16	
Passive usage	660	9.13 (3.57)	00-16	
Emotional Investment	660	30.2 (6.53)	13-48	0.866
SWL	660	19.1 (6.18)	5-30	0.905

ANSU: Active non-social usage; SWL: Satisfaction with life; Q: Quarter

Table 1 Descriptive characteristics (N=660)

Measure

The survey included ad-hoc sections and standardized questions. There were three sections, detailed below.

Section A contains questions related to social-demographic characteristics and health status. Participants were asked about their gender (male and female), location (State), and chronic disease (Yes or No). The purpose of asking the chronic disease-related questions is to ensure the participants should not be diseased with any chronic disease and perfectly fit at the time of the survey.

Total time spent on social media (TTSSM)

The TTSSM was calculated through an Android application. The total time was calculated as the summation of time spent on every social networking platform. In this study, the total amount of time spent on Facebook and Instagram was considered for further analysis.

Active-Passive usage of social media

Section B contains questions related to active and passive social media use (Gerson et.al., 2017) and social media usage. Passive active use measure (PAUM) is a Facebook use questionnaire with 13 items designed to identify the Facebook user's engagement activity. Respondents were asked to report their engagement activities using a 5-point Likert scale (1-never, 5-very frequently). Gerson et.al. (2017) found that the uses of Facebook can be classified into three subscales: active social use, ANSU, and passive use.

EI in social media

Next in line, section B comprises questions related to the social media use integration Scale for EI (Jenkins-Guarnieri et al., 2013). This scale includes a 10-item measure of self-reporting used to measure two-dimension termed Social Integration and Emotional Connection (SIEC) and Integration into Social Routines (ISR). Making use of a 5-point Likert scale, the respondents are asked to report their levels of EI (1 = Strongly disagree, 5 = Strongly agree). The Social Media Use Integration Scale reported decent reliability with Cronbach's alpha of .89. The reliability of the current sample was reported with Cronbach's alpha of .866.

Satisfaction with life

Satisfaction with life is measured through 5-item satisfaction with life scale developed by Diener et al. (1985) to assess overall judgment of one's life. Participants were asked to report their responses to each of the seven questions on a 7-point Likert scale ranging from 1 to 7 (1-Strongly disagree, 7-strongly agree). The scores were added for total scores representing low scores for the low level of life satisfaction and high score for the high level of life satisfaction. The scale has demonstrated excellent internal consistency (α = .905) in the current study.

Statistical Analyses and Results

The statistical analysis was conducted using SPSS version 26 and Jamovi 2.2.5 based on R statistical tool (IBM, Armonk, NY, USA; Jamovi Project, 2021) to perform descriptive statistics analyses, reliability analyses, and bivariate correlation.

Non-parametric bootstrapping analysis (Preacher & Hayes, 2004) was used to assess the sequential mediation model of EI as mediators of the relationship between TTSSM, active, passive, ANSU, and satisfaction with life respectively. This was done to prevent over-inflated indirect effects (Hayes, 2012). Demographic variables such as age, gender, and education are considered covariates. For the direct, indirect, and combined impacts of each kind of TTSSM, active, passive, ANSU, on satisfaction with life, 5000 bootstrap samples were used to calculate standard errors and 95% confidence intervals (CI). This intermediate analysis is crucial if 95% of the indirect impacts of the CI deviation's correction and acceleration (lower limit, LL, and upper limit, UL) do not contain 0 (Preacher et al., 2007, Preacher & Hayes, 2004).

For assessing both direct and indirect hypothesized associations, the four Serial Mediation Model (SMM) in SPSS Model 6 was employed using the Hayes process macro (Hayes, 2012). This approach, which does not need a normal distribution of samples, offers a more precise estimate of indirect effects than the Sobel test based on normal theory (Hayes, 2012).

Preliminary Analyses

Current cross-sectional studies use data from a single source, not with standing its limitations. The researchers examined the challenges with cross-section data in mediation analysis and quantified statistical bias by evaluating the influence of longitudinal mediation effects on this type of data (Maxwell et.al., 2011). They also examined the impacts of longitudinal mediation effects on this kind of data. According to Baron & Kenny (1986), if the temporal ordering of the variables was known, it may be helpful to investigate mediation analysis on cross-sectional data. EI (M1), for instance, in the current investigation, might explain the effect of TTSSM (X) on SWL (Y) (SMM1), active (X) on SWL (Y) (SMM2), passive (X) on SWL (Y)(SMM3), ANSU (X) on SWL (Y)(SMM4), if the observed variables represent quasi-instantaneous processes. The variance, skewness, and kurtosis were computed and were within acceptable bounds; specifically, the ranges for skewness and kurtosis are respectively -3 to +3 and -10 to +10 (Brown & Marshall, 2006).

Correlational Analysis

Table 2 represents correlation analysis and scale reliability. The correlation results indicated that TTSSM was negatively associated satisfaction with life (r = -.666, $p < 0.01$). whereas positively associated with EI (r = .425, $p < 0.01$). This result indicates that when an individual spends more time on social media, it increases more EI and diminishes their satisfaction with life. Furthermore, it was also found that TTSSM was also associated with active (r = .119, $p < 0.01$), passive (r = .278, $p < 0.01$), and ANSU (r = .258, $p < 0.01$) usage of social media.

	TTSSM	Age	Gender	Active	ANSU	Passive	EI	SWL
TTSSM	1							
Age	-.645**	1						
Gender	.030	-.051	1					
Active	.119**	-.083*	-.069	1				
ANSU	.258**	-.143**	-.030	.518**	1			
Passive	.278**	-.184**	.020	.558**	.449**	1		
EI	.425**	-.249**	-.004	.188**	.315**	.348**	1	
SWL	-.666**	.449**	-.025	-.163**	-.194**	-.250**	-.304**	1

Note. ∗ p ≤ .05, ∗∗p ≤ .01, ∗∗∗p ≤ .001.
ANSU: Active non-social usage; TTSSM: time spent on social media, EI: emotional investment, SWL: Satisfaction with life

Table 2 Person correlation between various construct

Covariates

Age was negatively associated with TTSSM (r = -.645, $p < 0.01$), active (r = -.083, $p < 0.05$), ANSU (r = -.143, $p < 0.01$), passive (r = -.184, $p < 0.01$) and EI (r = -.249, $p < 0.01$) whereas positively associated with SWL (r = .449, $p < 0.01$). Gender was not significantly associated with any other factor. Age and gender were considered covariates when estimating the mediation analysis.

Regression Analysis

Non-parametric bootstrapping was used to test the indirect effect. If the null or 0 occurs within the lower and upper bounds of the 95 percent confidence interval, the population indirect impact is assumed to be 0. If 0 falls beyond the confidence interval, it is assumed that the indirect effect is non-zero.

From serial mediation model 1 (represented in Table 3), it was revealed that there was a significant direct effect of TTSSM on EI ($\beta = 3.38, p < 0.01$) and SWL ($\beta = -4.82, p < 0.01$). Hence hypothesis H1 is accepted. From SMM 2, it was found that there was a significant direct effect of active users of social media on EI ($\beta = .268, p < 0.01$) and SWL ($\beta = -.198, p < 0.01$), whereas EI also influencing directly to SWL ($\beta = -.206, p < 0.01$). Therefore, H2 (a) is rejected. As per

SMM3, it was found that there was a significant effect of passive usage of social media on EI (β = .634, $p < 0.01$) and SWL (β = -.280, $p < 0.01$), whereas EI directly influencing SWL (β = -.185, $p < 0.01$), hence H2 (c) is accepted. Lastly from SMM4, it was revealed that there is a direct effect of ANSU on EI (β = .622, $p < 0.01$) and SWL (β = -.197, $p < 0.05$), whereas EI directly influences SWL (β = -.207, $p < 0.01$) Hence, H2 (b) is rejected.

Direct effect	**Estimate**	**SE**	***T (LL-UL)***
SMM 1: TTSSM →EI →SWL			
TTSSM → EI	3.38**	.281	12.03(2.83 - 3.93)
TTSSM → SWL	-4.82**	.249	-19.32 (-5.31 - -4.33)
EI → SWL	-.016	.030	-.551 (-.077 -.043)
SMM 2: ACT → EI →SWL			
ACT → EI	.268**	.054	4.91(.161 - .375)
ACT → SWL	-.198**	.050	-3.96 (-.297 - -.100)
EI → SWL	-.206**	.036	-5.70 (-.277 - -.135)
SMM 3: Passive → EI →SWL			
Passive → EI	.634**	.066	9.51 (.503 - .765)
Passive → SWL	-.280**	.066	-4.24 (-.410 - -.151)
EI → SWL	-.185**	.037	-4.95 (-.258 - -.111)
SMM 4: ANSU → EI →SWL			
ANSU → EI	.622**	.073	8.50 (.478 - .766)
ANSU → SWL	-.197*	.071	-2.76 (-.337 - -056)
EI → SWL	-.207**	.037	-5.58 (-.280 - -.134)

$N = 660$, $^{*}p < 0.05$, $^{**}p < 0.01$.

ACT: Active usage; ANSU: Active non-social usage; TTSSM: time spent on social media, EI: emotional investment, SWL: Satisfaction with life

Table 3 Direct effects for the paths on the SMMs

Additionally, it was found from SMM1 that there was no indirect effect of TTSSM on SWL through EI (Table 4). Therefore, hypothesis H3 is accepted. However, from SMM2, SMM3 & SMM4, it was found there was a significant indirect effect of active (IE = -.016, 95% CI, LL = -.028 – UL = -.007), passive (IE = -.031, 95% CI, LL = -.050 – UL = -.015) and active non-social usage (IE = -.029, 95% CI, LL = -.048 – UL = -.014) on SWL through EI respectively. Therefore, H4 (a,b & c) was rejected.

	Effect	SE	LL	UL
SMM 1: TTSSM →EI →SWL				
Total	-.195	.126	-.456	.050
TTSSM →EI → SWL	-.057	.118	-.296	.169
TTSSM → EI →SWL	-.026	.017	-.065	.005
SMM 2: ACT → EI →SWL				
Total	-.219	.025	-.070	.026
ACT →EI → SWL	**-.055**	**.015**	**-.089**	**-.026**
ACT → EI →SWL	**-.016**	**.005**	**-.028**	**-.007**
SMM 3: Passive → EI →SWL				
Total	**-.150**	**.032**	**-.217**	**-.087**
Passive →EI → SWL	**-117**	**.028**	**-.177**	**-.064**
Passive → EI →→SWL	**-.031**	**.008**	**-.050**	**-.015**
SMM 4: ANSU → EI →SWL				
Total	**-.166**	**.033**	**-.236**	**-.104**
ANSU→EI → SWL	**-.129**	**.028**	**-.188**	**-.075**
ANSU → EI →SWL	**-.029**	**.008**	**-.048**	**-.014**

LL, Lower limit; SE, Standard error; UL, Upper limit. Paths in bold indicate statistically significant indirect effects.

ACT: Active usage; ANSU: Active non-social usage; TTSSM: time spent on social media, EI: emotional investment, SWL: Satisfaction with life

Table 4: Indirect effects and total effects for the paths on the SMMs (Serial Mediation Models)

Discussion

This study concentrated on two different aspects: a) the direct effect of TTSSM and active-passive social media usage on mental health, b) the serial mediation effect of TTSSM and active-passive usage on mental health through emotional investment. As per the result (table 2), it was found that TTSSM was positively associated with EI and negatively associated with SWL. As user spends more time on social media, they were more associated emotionally with social media which leads to diminished SWL. Later, TTSSM was also negatively related to age. In other words, as the age increases the time spent on social media decreases. Also, TTSSM also positively related to active, passive, and ANSU usage of social media. From the SMM1, it was revealed that TTSSM affects EI positively and SWL negatively. Although life satisfaction was not influenced by EI. It was also found that EI do not mediate the relationship between TTSSM and life satisfaction.

In a non conformity from the existing studies where the thrust was on the time of social media usage or active-passive involvement in it, the current study makes an important contribution that passive usage was more responsible for diminished life satisfaction rather than active and ANSU usage of social media. From the correlational analysis, it was found that passive usage was strongly negatively related to life satisfaction as compared to active use and ANSU. As per the SMM2, active usage was directly influencing EI. Additionally, EI also affect directly SWL. In other words, when an individual is active on social media, their EI was increased but at the same time, it decreases life satisfaction. Active usage directly affects life satisfaction negatively, due to some other factors that may be influencing the relationship between active usage and life satisfaction. As per the finding of SMM2, there was a significant mediation of EI in between active usage and life satisfaction. This is due to the high emotional involvement of people may induce negative emotions which changes the satisfaction with life.

Passive usage was an important factor that strongly impacted life satisfaction negatively and EI positively. Correlational analysis revealed that as age increases, passive usage decreases. In other words, older people used social media actively as compared to the younger age group. Passive usage by the people positively related to EI and negatively related to SWL. The primary reason for the poor life satisfaction was the high emotional involvement, which causes poor life satisfaction. The same findings were revealed from the SMM 3 in which there was a positive direct effect of passive usage on EI and a negative effect on SWL. There was an indirect effect of passive usage on SWL through EI.

Eventually, ANSU was negatively associated with SWL and age. In other words, as the age increases the probability of ANSU decreases. Older age group people mostly use social media passively or ANSU. ANSU was also positively related to EI. Even more, EI negatively mediate the relationship between ANSU and life satisfaction. That means whether any individual use social media actively, passively or ANSU, it always increases emotional involvement, which roots the cause for poor well-being. Generally, people spent time on social media for various purposes, for example, entertainment, information, education, social networking, etc. but unintentionally people were emotionally connected with their friends, acquaintances, and others. Due to the frequent use of social media, people may get information about others and give responses to the news to be more connected. People also expect the same response from others. However, if the same response or expectation was not fulfilled it induces negative emotions (envy, depression, and anxiety) and leads to poor life satisfaction.

Theoretically and practically, this study has implications for social media usage and life satisfaction. Previous research has primarily focused on the impact of social media time and active-passive usage on mental health. This study went one step further to investigate the relationship between the total time spent on social media/active-passive and ANSU usage, emotional perspectives, and an individual’s self-esteem.

Parents, educators, and health professionals will benefit from the current study. According to the findings of the current study, users should limit their social media usage; it should not be excessive, since this might have a negative impact on life satisfaction. It is also recommended that users use social media without much emotionally involved in it or use emotions in the right direction, which will aid in the individual's mental health. Emotional intelligence can be a solution to poor mental health and well-being which can be studied in the future. Counsellors and health practitioners can be consulted in this case.

There are a few limitations to this study that must be acknowledged at the time of result interpretation. Firstly, the total amount of time included in the study was from Facebook and Instagram, other social media network was not considered for analysis. Other networks like YouTube, Whatsapp, etc can be considered for investigation in future studies. The selection of the participants was non-probabilistic incidental. The participants were from India only; therefore, the findings may be limited to this country. Future studies can be conducted from various cultural perspectives as moderating or mediating variables.

Conclusion

The current study investigates the impact of social media usage, emotional investment on life satisfaction. The current study's findings present empirical reasoning and information related to social media by representing that combination of emotional investment, and self-esteem will impact life satisfaction. Previous studies investigated the impact of social media usage on mental health; however, this study is crucial and represents how social media usage impacts well-being (life satisfaction). This is the first study that demonstrates the role of EI between social media usage and life satisfaction. As a result, the current study's findings are significant and relevant in terms of implications for social media research and health professionals.

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