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Original research article

Social media disorder in relation to device screen time and autosuggested social media content engagement

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Abstract

Though emerging technology offers people a comfortable life, a few adverse effects also exist. There was a rapid increase in mobile phone usage and internet consumption during and post the Covid-19 pandemic, which reached the extent of addiction among youths. Thus, this study examines social media disorder among adolescents in relation to the time spent on a computer or smart-phone device screen and engaging in autosuggested social media content. The study included 235 responses from students in higher secondary schools of Bangalore, India. The study found a significant positive correlation between device screen time, autosuggested social media content engagement (ASMCE), and social media disorder. Multiple regression analysis indicated that 56.5% of social media disorder among adolescents is due to the time spent on a computer or smart phone device and autosuggested social media content engagement. The study did not measure any differences in social media disorder based on the demographic details of the study participants. As social media disorder affects the mental health of adolescents, especially in post pandemic times, and further affects their academic performance, the researchers suggest that future studies explore the other factors causing social media disorder.

Keywords: Autosuggested system; Mobile addiction; Social media disorder

Introduction

Over the last decade, there have been several studies on social media (Al-Bahrani et al., 2015; Bhumika et al., 2022; Kaya and Bicen, 2016; Kelm, 2011; Lau, 2017; Mccolgan and Paradis, 2022; Wang et al., 2011). With the rise of smartphone usage since 2012 (Twenge et al., 2018), studies pertaining to social media behaviour have increased. According to Boer et al. (2022), it will take time for the DSM-5 (Diagnostic and Statistical Manual of Mental Disorder) to recognise social media disorder, which studies point out can be similar to substance-related addictions (Griffiths, 2013; Griffiths et al., 2014). There are only a few specific diagnoses of "internet addiction" or "Gaming Disorder" and some examinations of the symptoms are drawn from a single social media platform (Bányai et al., 2017), thus failing to give us a clear picture of the term "Social Media Disorder" (Michikyan and Suárez-Orozco, 2016). According to Ergun and Alkan (2020), social media disorder is a behavioural addiction, which is accompanied by loneliness, depression, self-esteem issues, reduced sleep, and poor academic performance.

These days, the popular forms of social media among 18–25 year-olds are Instagram, Snapchat, and Twitter (Mccolgan and Paradis, 2022), and according to Hines (2022), Gen Y and Gen Z account for around 90.4% of social media use. Seeing examples of ideal body image on social media platforms like YouTube, Facebook, and Instagram is readily contributing to body image disorders (Vandenbosch et al., 2022). Studies have also reported that increased social media use in adolescents results in ADHD symptoms (Barry et al., 2017; Boer et al., 2020; Levine et al., 2007).

A correlation study between ADHD and social media use reported that internet addiction is a compulsive disorder (Meerkerk et al., 2009). Griffiths et al. (2013) found that students are addicted to specific activities on the internet, rather than just internet use. Internet gaming disorder is one such example, and although the manual of mental disorders does not include social media addiction, studies have shown otherwise (Pantic, 2014; Ryan et al., 2014).

Here, addiction refers to being constantly engaged in online activity, which has an adverse impact on other areas of life (Andreassen and Pallesen, 2014). The possibility of developing an addiction to the use of technology is present in anyone with immediate access to the internet (Kuss et al., 2014), but the younger demographic is more prone towards it (Kuss et al., 2014; van Deursen et al., 2015). Research has also demonstrated that while both men and women can become 'addicted' to technology, they use different online activities (Kuss et al., 2014). Males are more likely to become 'addicted' to on-

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line video gaming, cyber-pornography, and online gambling, while females tend to develop addictions to social media, texting, and creating an online presence (Maraz et al., 2015; van Deursen et al., 2015). Today's students spend less time engaged in outdoor activities, and even when they are outdoors they spend most of their time on electronic gadgets (Larson et al., 2019). The emergence of COVID-19, schools being shut down, and lockdown restrictions (Ghosh et al., 2020; Patel et al., 2021) resulted in the transition to online classes. As a consequence, there was an increase in screen time that went beyond the recommended duration of two hours (Nagata et al., 2020; Schmidt et al., 2020; Vardoulakis et al., 2020). This increased screen time can result in adverse health impacts (Barnett et al., 2018; Hale et al., 2018; Rosen et al., 2014). A study conducted by Moitra and Madan (2022) revealed that adolescents in India spend around 65% of their device-screen-time on social media entertaining themselves, and only use it for academic purposes 35% of the time. According to a systematic review by Zhang et al. (2022), screen time also leads to psycho-behavioral problems, myopia, and other health impacts. A study conducted on UG medical students in China showed that a combination of screen time and physical activity affects the stress level of students. Students who spend less time on device-screens and more time engaged in physical activity have less stress (Ge et al., 2020).

School is an ideal environment to promote a healthy lifestyle in children (Sevil et al., 2019), but school interventions tend to target only single health behaviours rather than multiple behaviours such as screen time, sleep, diet, and physical activity (Cotton et al., 2020). According to Busch et al. (2013), multiple health behaviour change interventions are better than single-behaviour interventions. Hence, the aim of this study is to ensure that schools promote a healthy lifestyle for the students, and look at ways to moderate screen time and help students to disable autosuggested content features. Excessive social media use and addiction to browsing autosuggested social media content might create behavioural disorder among adolescents. The present study aims to measure the relationship between device screen time, autosuggested social media content engagement, and social media disorder. Thereby creating awareness among parents, teachers, health professionals, and policy makers to take care of the younger generation, especially in the Indian context – which is among the highest youth populated countries in the world. These relationships might also hold true to many other middle-income countries, and the study implications might help the situation.

Theoretical framework

The present study has emerged from the social effects of computer-mediated communication, and is guided by the SIDE model (Social identity model of deindividuation effects) (Lea et al., 2001). Adolescents disguise themselves on social media pages using incognito mode and demonstrate antinormative behaviour. An individual's online and offline identity differ. According to Uses and Gratification Theory (UGT), individuals seek out specific mass media communication to satisfy themselves.

Therefore, the AI enabled autosuggestion system allows such individuals to gratify themselves with the suggested media content (Menon, 2022), which in turn increases screen time. As per media dependency theory, if an individual meets their needs through media, this becomes a significant part of their life (Ball-Rokeach and DeFleur, 1976), which can then lead to addiction and eventually behavioural disorder.

Context of the study

In the new normal, particularly in low-income countries like India, browsing social media apps on smart phones or personal computers represents an easily accessible entertainment or leisure time activity for adolescents. Typically, they use Youtube, Netflix, gaming channels, short videos, Instagram-reels, snapchats, and Facebook. The pandemic forced parents to give their children a smart phone or laptop for online classes. Post-pandemic, these devices became their favourite way to access social media and gratify themselves with e-entertainment. Metro city like Bangalore has adolescents whose parents are employed and therefore they could afford buying devices like smartphone or laptop with internet connection to their children.

Many parents also used smart phones/computers/televisions as a way to engage their kids and stop them from disturbing them. This led to rampant mobile usage by adolescents on social media channels, culminating in behavioural disorders and addiction. The disorders, which are basically, the feeling of loneliness, depression, low self-esteem, poor sleeping habits, and low academic performance, became quite common. Thus, the present study aimed to understand the relationship between social media disorder, device screen time, and autosuggested social media content engagement among higher secondary school students. If the relationship proves positive, then all parents and educational stakeholders may realise the adverse effect of social media usage.

Research question

How does the relationship between device screen time, engagement with autosuggested social media content, and social media disorder manifest in higher secondary school students?

Objectives

1. To find the relationship between device screen time and autosuggested social media content engagement.
2. To find the relationship between device screen time and social media disorder.
3. To find the relationship between social media disorder and autosuggested social media content engagement.
4. To discover to what extent the time spent on a computer and/or smart phone screen, and autosuggested social media content engagement predict social media disorder.

Materials and methods

The study employed a descriptive correlational design to address the research questions raised. The survey questionnaire was sent to 300 students, and 235 successful responses were obtained from higher secondary schools across Bangalore, India. The participants' age ranged from 16 to 17 with a diverse background. The study used the autosuggested social media content engagement scale, developed by the researchers, and the social media disorder scale, developed by Van Den Eijnden et al. (2016) and revalidated further by Boer et al. (2022). The survey participants also mentioned the amount of time they spent on their devices using social media, and how much time they spent using their devices for academic purposes. The researchers constructed a scale to measure the students' engagement with autosuggested social media content. Table 1 presents the items of the constructed scale. The scale measuring autosuggested social media content engagement had five items with a 4-point response options; never, sometimes, often, and always. Three experts in the field validated the scale.

A pilot study data tested by Cronbach alpha internal consistency test, found the coefficient value of 0.745, indicating that the score is highly reliable (Nunnally, 1978). The instrument contained an informed consent form at the beginning of the survey with a note on the anonymity and confidentiality of the data. The researchers encrypted the data and stored it in a password-protected file, ensuring it is accessible only to the researchers. The researchers imported the data to SPSS software to conduct the data analysis. They also sought institutional review board clearance from the university to conduct this significant research work.

Table 1. Autosuggested social media content engagement scale (ASMCES)

Instructions
Respond to the following items by choosing any one of the four options provided on a 4-point Likert scale Never – 1, Sometimes – 2, Often – 3, Always – 4
Items
• I follow autosuggested content while watching reels/ short videos/ other media sites on a mobile device
• I find autosuggested content on social media more relevant
• I mostly like and subscribe to autosuggested content while on social media
• I like navigating through autosuggested content on social media pages
• Autosuggested content on social media pages satisfies my need

Results

Descriptive statistics of the data indicate that, out of 235 survey participants, 90 are suffering from social media disorder, which is almost 40% – as shown in Fig. 1.

The researchers' conducted Pearson's product-moment correlation test and multiple regression statistical analysis to test the study hypotheses. Table 2 presents the result of the correlation test.

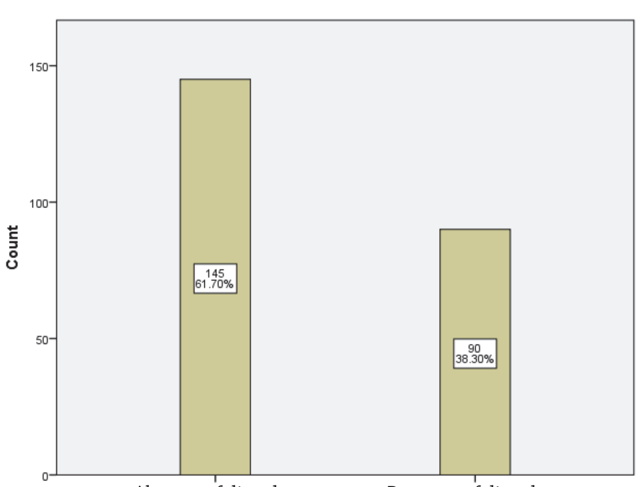

Fig. 1. Histogram of social media disorder

Table 2. Pearson product-moment correlation statistics

Correlation between	Pearson product-moment correlation coefficient
Device screen time and autosuggested social media content engagement	0.376**
Social media disorder and device screen time	0.757**
Social media disorder and autosuggested social media content engagement	0.412**

Note: ** Correlation is significant at the 0.01 level (2-tailed).

Table 2 shows that Pearson's product-moment correlation test reported a correlation coefficient value of 0.376 and is significant at the 0.01 level (2-tailed). This indicates a significant moderate positive correlation between device screen time and autosuggested social media content engagement among higher secondary school students.

Pearson's product-moment correlation test reported a correlation coefficient value of 0.757 and is significant at 0.01 level (2-tailed). This indicates a strong positive correlation between device screen time and social media disorder among higher secondary school students.

Pearson's product-moment correlation test reported a correlation coefficient value of 0.412 and is significant at 0.01 level (2-tailed). This indicates a moderate positive correlation between social media disorder and autosuggested social media content engagement among higher secondary school students.

Multiple regression analysis

The researchers conducted multiple regression statistical analysis to understand the variation in social media disorder (dependent variable) as explained by device screen time and autosuggested social media content engagement (independent variables). Table 3 presents the model summary of multiple regression analysis.

Table 3 also demonstrates a correlation ($R = 0.754$) between social media disorder, the independent variables device screen time, and autosuggested social media content engagement among higher secondary school students. Together, device screen time and autosuggested social media content engagement (independent variables) accounted for 56.5% variation in social media disorder (dependent variable). In addition, a Durbin–Watson statistics value of 2.404 indicates that there is no first order autocorrelation. It also indicates that the model fit established between dependent variables and independent variables will remain true in the future, and predicts the magnitude of social media disorder for the varied device screen time and autosuggested content engagement values.

Table 4 shows the result of ANOVA statistics ($F = 152.737$, $p < 0.05$), and explains how well the independent variables – device screen time and autosuggested social media content engagement influence the dependent variable – social media disorder among higher secondary school students.

Table 3. Model summary statistics of multiple regression analysis

Model	R	R Square	Adjusted R Square	Std. error of the estimate	Durbin–Watson
1	0.754[a]	0.568	0.565	1.788	2.404

[a] Predictors: (Constant), device screen time and autosuggested social media content engagement.

Table 4. ANOVA statistics

ANOVA[a]

Model		Sum of squares	df	Mean square	F	Sig.
1	Multiple regression	976.112	2	488.056	152.737	0.000[b]
	Residual	741.335	232	3.195		
	Total	1717.447	234			

[a] Dependent variable: social media disorder. [b] Predictors: (constant), device screen time and autosuggested social media content engagement.

The multiple regression model coefficients presented in Table 5 determine whether independent variables – device screen time and autosuggested social media content engagement – together statistically significantly contribute to the model. The study framed the following multiple regression equation from the unstandardized coefficients (B) values to show the prediction of social media disorder from the independent variables – device screen time and autosuggested social media content engagement.

Table 5. Multiple regression coefficients statistics

Coefficients[a]

Model		Unstandardized coefficients		Standardized coefficients	t	Sig. lower bound	95.0% Confidence interval for B	
		B	Std. error	Beta			Lower bound	Upper bound
1	(Constant)	–1.156	0.424		–2.726	0.007	–1.991	–0.320
	Device screen time	0.038	0.002	0.710	15.324	0.000	0.033	0.043
	Autosuggested Social media content engagement	0.101	0.045	0.104	2.234	0.026	0.012	0.190

[a] Dependent variable: social media disorder.

Multiple regression equation

$$\text{Social media disorder} = -1.156 + (0.038 \times \text{Device screen time}) + (0.101 \times \text{ASMCE})$$

Fig. 2 shows frequency distribution of the standardized residuals for the dependent variable social media disorder.

Fig. 3 shows a scatterplot of multiple regression analysis. The scatterplot shows the equal variances of data distribution from the given population.

According to this, device screen time and autosuggested social media content engagement are significant predictors of social media disorder among higher secondary school students, accounting for 56.5% variation.

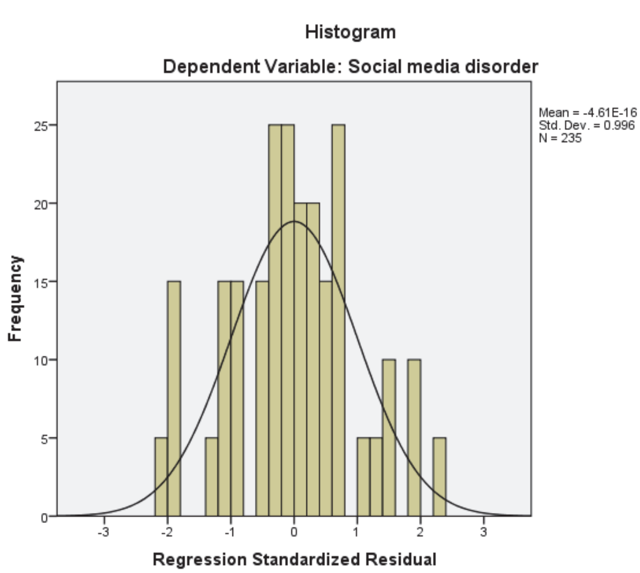

Fig. 2. Histogram of multiple regression

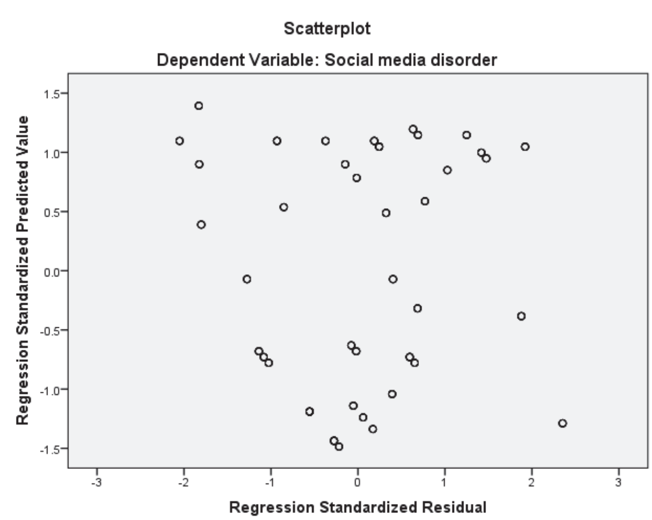

Fig. 3. Scatterplot for multiple regression

Discussion

The study results showed a strong positive relationship between device screen time and social media disorder. An earlier study also indicated a positive correlation between screen time and other mental disorders, including social media addiction (Hjetland et al., 2021; Lissak, 2018). The reason many are constantly engaged in social media is the release of dopamine and oxytocin (Seiter, 2016). Reels and TikToks created by content makers are designed to cater to a shorter attention span of social media consumers, which ensures users are constantly engaged (Sandikar, 2021). Auto suggested content is a default feature that is turned on in any device, and people lack knowledge on where to turn it off. The suggestions come from internet data based on the user's browsing history and its understanding of consumer behaviour. Thus the content easily engages people, leading to increased screen time and contributing to social media disorder.

The results indicate a moderate positive relationship between autosuggested social media content engagement and social media disorder.

Out of the 235 survey participants, 90 were suffering from social media disorder, which is almost 40%. In the post-pandemic context, adolescents living in metropolitan cities like Bangalore have easy access to a smart phone or laptop and are using these to entertain themselves on social media, which invariably increases screen time and engagement with autosuggested social media content. This leads to social media disorder and other mental health issues. As adolescents, they have no control over their action when it comes to playing or watching social media on smart phones/personal computers. Our study participants revealed an average screen time of one and a half hours. This is essentially a matter of concern for parents and teachers, because it is affecting students' academic performance as well as their mental health (Adelantado-Renau et al., 2019a; Horowitz-Kraus and Hutton, 2018; Kim et al., 2020; Wang et al., 2019).

Artificial intelligence enabled autosuggested systems are capturing the attention of young adolescents, thereby contributing to increased screen time. In the current study, autosuggested social media content is moderately correlated to social media disorder. This trend may increase in the near future, causing internet addiction (Zhao, 2021) and other behavioural disorders. Though the autosuggestion option can be turned off on social media pages, due to a lack of awareness, most adolescents do not seem to do so. In order to curb social media addiction and disorder, schools and colleges must educate students on positive and healthy ways to use social media platforms.

If parents, teachers, and stakeholders do not monitor its fair usage, they will suffer consequences like behavioural disorder (Boers et al., 2019; Slobodin et al., 2019), low academic performance (Adelantado-Renau et al., 2019b), internet addiction (Aşut et al., 2019), etc. India is a developing country and not all parents are tech savvy. Therefore, students have more knowledge of smart phone and internet sites than their parents. Students engage in deceptive behaviour with their parents, feigning study time while secretly indulging in social media. It is important to promote open communication and honesty between students and their parents to foster trust and ensure a healthy academic environment.

In order to curb the spread of the disorder among adolescents, policy makers, cyber industries, AI programmers, teachers, school administrators, and all related stakeholders must take stock of the situation and ensure measures for adolescents' wellbeing. While the study reported that almost 40% of the sample are addicted to social media, the average social media disorder score is 3.94, which is close to the cut-off score of 5. In the near future, the average score may increase, and we may see a day where most youths suffer from social media disorder.

Another important observation is that adolescents spend an average of 1.5 hours per day on social media; this is a lot and affects their productivity as students. Screen time can also cause other behavioural disorders like exhaustion, anxiety, stress, and depression.

Conclusion

The present study found a relationship between device screen time, autosuggested social media content engagement, and social media disorder. A moderate relationship was revealed between device screen time and autosuggested social media content engagement among higher secondary school students. A moderate relationship was found between students engaging in autosuggested social media content and social media disorder. A strong correlation between device screen time and social media disorder was also discovered. The study only included participants studying in higher secondary schools. The present study is unique, as it discusses the factors affecting social media disorder in the post-pandemic context. As smart mobile phones and the internet are cheaply available and accessible, Indian youths are falling prey to social media addiction. Without the necessary precautions, this could lead to dangerous consequences in relation to the workforce, education, and the economic prosperity of the country.

Ethical aspects and conflict of interests
The authors have no conflict of interests to declare and contributed equally to the study.

Závislost způsobená časem stráveným na sociálních sítích v souvislosti s automaticky generovaným obsahem na sociálních sítích

Souhrn

Přestože vznikající technologie nabízejí lidem pohodlný život, existuje také několik nepříznivých účinků. Během pandemie covidu-19 a po ní došlo k rychlému nárůstu používání mobilních telefonů a internetu, což vedlo k závislosti u mladých lidí. Tato studie tedy zkoumá poruchy v kontextu sociálních médií mezi dospívajícími ve vztahu k času strávenému na obrazovce počítače nebo chytrého telefonu a zapojení se do automaticky navrhovaného obsahu sociálních médií. Studie zahrnovala 235 odpovědí od studentů vyšších středních škol v Bengalúru v Indii. Studie zjistila významnou pozitivní korelaci mezi dobou strávenou na zařízení, automatickým zapojením obsahu sociálních médií (ASMCE) a poruchou v kontextu sociálních médií. Vícenásobná regresní analýza ukázala, že 56,5 % poruch v kontextu sociálních médií mezi dospívajícími je způsobeno časem stráveným na počítači nebo chytrém telefonu a automaticky navrženým zapojením obsahu sociálních médií. Studie nezměřila žádné rozdíly v poruchách sociálních médií na základě demografických údajů účastníků studie. Vzhledem k tomu, že porucha v kontextu sociálních médií ovlivňuje duševní zdraví dospívajících, zejména v době po pandemii, a dále ovlivňuje jejich akademický výkon, vědci navrhují, aby budoucí studie prozkoumaly další faktory způsobující poruchy v kontextu sociálních médií.

Klíčová slova: automaticky navrhovaný systém; závislost na mobilních zařízeních; závislost na sociálních sítích (social media disorder)

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