The International Journal of Indian Psychology
ISSN 2348-5396 (Online) | ISSN: 2349-3429 (Print)
Volume 13, Issue 3, July- September, 2025
DIP: 18.01.088.20251303, DOI: 10.25215/1303.088
https://www.ijip.in

Research Paper

Algorithms, Addiction and Self-Esteem: Psychological Resilience in the Meta Era

Ramona Sharma[1]*, Shaina Bedi[2]

ABSTRACT

In the Meta Era, every decision and desire is shaped by unseen codes that predict our next move with great precision. Social Media algorithms have become like pervasive all-knowing entities that anticipate, influence, and ultimately dictate our reality. This paper aims to examine the relationship between exposure to recommendation algorithms on social media and psychological resilience, specifically focusing on social media addiction (SMA) and self-esteem. This research employs a quantitative methodology. An online survey was used to collect data from 150 participants aged 18-24, selected via convenience and snowball sampling. It combines the Bergen Social Media Addiction Scale (BSMAS) [Andreassen et al., 2016], Rosenberg Self-Esteem Scale (RSES) [Rosenberg; 1965] and Brief Resilience Scale [BRS; Smith et al., 2008]. Exposure to recommendation algorithms is measured based on self-reported data on the total time spent engaging with recommended content on social media. The above data was statistically analysed using Spearman's Correlation and Linear regression through SPSS Software. This study aims to contribute to the limited research on the intersection of persuasive technology and psychology. It seeks to highlight the implications of algorithm-driven content and influencer trends on compulsive buying and digital consumerism, using the Fogg Behaviour Model [Fogg, B., 2009]. This study will also explore the significant impacts of widespread disinformation on social media and its role in fuelling societal polarisation. By addressing these issues, this paper ultimately calls for digital interventions and regulation of social media usage, to break the cycle of behavioural addiction.

Keywords: *Recommendation Algorithms, Social Media Addiction, Psychological Resilience, Self-Esteem, Digital Consumerism*

According to Van Lang, Paul A.M., et al. (2012) social dilemmas are defined as the conflicts between self-interest and collective interest. In the context of social media usage, the meaning can be imposed through the competition between social media apps to keep consumers hooked to the screen for as long as possible to monetise their time and attention (Orlowski, 2020, 0:13:28).

[1]Jai Hind College, University of Mumbai, Maharashtra, India
[2]Jai Hind College, University of Mumbai, Maharashtra, India
*Corresponding Author

Received: May 11, 2025; Revision Received: July 23, 2025; Accepted: July 28, 2025

In the era of artificial intelligence (AI), algorithms are substituting human decision-making by using recommendation systems that learn through the users' past activities and behaviours and apply the best solutions to keep them engaged (Zhang & Liu, 2021). With features like infinite scroll and the "like" button, social media competes for our time and exploits our dopamine-driven desire for social validation, until we become habitual users (Atalatti & Pawar, 2024).

Aza Raskin, the inventor of the infinite scroll feature, estimated 200,000 lifetimes being wasted daily due to scrolling (Frankel, 2024) while Snap CEO Evan Spiegel admitted that social media fuels fake news (Garfield, 2017). Furthermore, the rise of social media usage has led to a plethora of mental health issues including anxiety, depression, loneliness, body image issues and thoughts of self-harm (Sadagheyani & Tatari, 2020). Envy, social comparison, and the fear of missing out, popularly abbreviated as "FOMO" are prevalent, especially among the youth (Abi Jaoude, E, et al, 2020, P. E137). The exploitative nature of these algorithms serves as a serious threat to Gen Z's resilience and ability to cope with emotional and social issues while also severely impacting their self-esteem (Bilgin and Taş, 2018).

This paper aims to conduct a detailed analysis of social media usage in young adults, understanding the subsequent role of self-esteem and psychological resilience. The results are based on data harvested through past literature and a self-designed survey, using psychological scale and statistical analysis. Further, the paper makes recommendations on how to combat this problem through the lens of the Indian youth in the context of Indian policymaking.

Fogg-Hook Behaviour Model

Ali et al. (2023) proposed a hybrid Fogg-Hook Behaviour Model, used by addictive social media algorithms. These algorithms run on habit loops, which prompt the human brain to engage in certain behaviours in anticipation of rewards. The Hook Behaviour Model (HBM) explains habit formation in four stages: *Triggers*, which prompt action; *Routine*, where the behaviour becomes automatic and turns into a habit; *Variable Rewards,* which maintain the behaviour through the brain's anticipation of a reward; and *Investment,* engaging triggers and exciting rewards that make the brain invest time and effort into sustaining the behaviour (Eyal, 2014). The Fogg Behaviour Model (FBM) explains habit formation in 3 steps: *Motivation*, where necessities or rewards drive human behaviour; *Simplicity,* the ability or ease of performing the behaviour; and *Trigger,* cues that prompt action (Fogg, 2009).

The combined model explains the working of addictive algorithms on social media by first identifying user behaviours based on their interests and environment to understand their motivations. These activities are further simplified, making social media more accessible and user-friendly. Triggers, such as notifications, are used to draw the user's attention and set them into a routine, making their behaviour of engaging with social media automatic. Variable rewards such as likes or mentions lead to brain excitement, which further leads to addiction. Investment is the final phase, involving extra features that keep the users committed to the social media applications, ensuring their return and encouraging them to invite new users.

Figure No. 1: The Fogg-Hook Behaviour Model (Ali et al., 2023)

Neurological Effects

Dopamine is a neurotransmitter, involved in the brain's reward system, responsible for the feelings of pleasure, satisfaction and motivation. Dopamine rewards us for beneficial behaviours and motivates us to repeat them (Watson, 2024). Studies by cognitive neuroscientists have shown that rewarding social stimuli activate the same dopaminergic reward pathways.

The Reward Prediction Error Encoding explains how maintaining a balance between positive and negative outcomes keeps our brains engaged, a principle effectively utilised by casino slot machines (Trevor Haynes, 2018). The Variable Reward Schedule further explains that if we perceive a reward to be delivered at random, and if checking for the reward comes at little cost, we tend to check for it habitually (Ferster and Skinner, 1957). These dopamine-driven cycles serve as a major foundation for how social media algorithms are designed to keep users hooked.

A study by Mujica et al. (2022), shows how most social media applications work on "addiction by design" using data-driven predictions about the users combined with an addictive interface design for algorithmic content curation. It takes advantage of the "dopamine cycle" which starts from "wanting" or craving stimulation (usually arising from boredom) and leads to "seeking" such stimulating behaviours. The users then "anticipate" potential rewards and respond to "triggers" that signal that the rewards might be near. The cycle ends with the "rewards" being consumed. The most addictive cycles happen when the desired rewards are irregular and unpredictable (Variable Ratio Schedule; Ferster and Skinner, 1957).

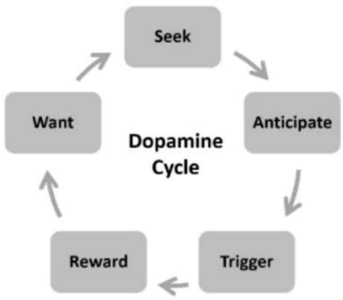

Figure No. 2: Dopamine Cycle (Mujica et al., 2022)

Further, various studies in cognitive neuroscience on humans and animals have shown that positive social interactions such as peer validation can lead to higher dopaminergic drive than when an addicted person gets access to drugs (Sinha and Shaikh, 2020). This concept plays a major role in the design of social media applications where several features such as the like and comment features, play on the users' psychological need for social validation.

Self-Esteem

Research has shown that social media users prefer to share activities that reflect the most pleasant parts of their lives with the hope of receiving positive responses from others (Kim & Lee, 2011).

Social media allows individuals to make social comparisons more easily and frequently. Moningka and Eminiar (2020) identified a negative correlation between social comparisons on social media and self-esteem, suggesting individuals who frequently compare themselves through social media are more likely to have lower self-esteem. These findings strengthen the evidence of the negative impacts of social media on adolescents and young adults.

Further, a study by Malik, P. 2024 in the Indian context, reported a similar negative correlation between social media usage and self-esteem, as well as between conflict and self-esteem, measured using the Rosenberg Self Esteem Scale. The findings suggest that individuals with higher social media usage are more likely to experience lower self-esteem, which can be associated with addictive behaviours and internal conflict. Further, conflict and relapse demonstrated significant negative correlations with self-esteem, indicating that lower self-esteem is linked to higher levels of internal conflict and an increased risk of relapse.

Resilience

Recent studies have highlighted the role of psychological resilience as a preventive factor against the negative impacts of social media usage. Problematic social networking site use (PSNSU), refers to the excessive and compulsive use of social networking sites (SNS) that lead to negative consequences in an individual's personal, social, or professional life (Andreassen & Pallesen, 2014). Zaheer Hussain and Wegmann (2021) found that resilience levels were negatively correlated with PSNSU severity, suggesting that higher resilience can help reduce the likelihood of PSNSU, especially among individuals with high anxiety, or ADHD, which were identified as risk factors for PSNSU. According to Hou et al. (2017), perceived stress among 499 Chinese college students was strongly linked to PSNSU, especially among those with lower resilience levels. Their study suggested that enhancing resilience can decrease the likelihood of PSNSU among students experiencing higher levels of stress. In a study by Bilgin and Taş (2018) individuals with higher psychological resilience and perceived social support were found less likely to develop addiction to social media, while the lack of both leads to unhealthy coping mechanisms such as social media addiction.

Existing research highlights how social media platforms exploit the psychology and brain structures of users to sustain their attention. However, critical gaps persist in understanding the role of algorithmically recommended content in influencing mental health. Further, while previous studies have explored social media addiction, self-esteem and psychological resilience extensively, their interconnected dynamic with algorithm-driven consumption remains less explored. There is a lack of empirical evidence for examining these results through behavioural frameworks such as the Fogg-Hook Behaviour Model.

This paper aims to contribute to the limited research on the intersection of persuasive technology, psychology, and neuroscience. It examines the effects of time spent engaging with algorithmically recommended content on social media addiction, self-esteem and psychological resilience, and provides insights into the underlying cognitive mechanisms shaped by digital interactions. The study builds upon the theories of behavioural addiction, self-concept and resilience, by offering an understanding of how algorithms exploit psychological tendencies to shape user behaviour. Further, it highlights the practical implications of social media addiction especially among youth, including the spread of misinformation and trends in influencer culture, which fuel societal polarisation and toxic consumerism. Ultimately, it calls for policy interventions and regulation, to break the cycle of behavioural addiction.

Research Problem

Is there a relationship between time spent engaging with algorithmically recommended content on social media and the severity of social media addiction? What are the impacts of SMA on an individual's self-esteem and what role does psychological resilience play in moderating this relationship?

Objective

- To study the relationship between time spent engaging with algorithm-driven recommended content on social media and social media addiction
- To study the role of social media addiction, driven by recommendation algorithms on an individual's self-esteem
- To study the role of psychological resilience in mediating the impact of social media addiction on self-esteem.

METHODOLOGY

This cross-sectional study employs a quantitative methodology using a survey-based method.

Sample

The sample consisted of 150 participants (N=150) out of which, 99 were females and 51 were males. The age of the participants ranged between 18-24 years.

The participants voluntarily filled out the online survey. The eligibility criteria required participants to be active users of social media, Indian citizens, and aged between 18-24. These criteria were mentioned at the beginning of the survey along with a consent form. Confidentiality and anonymity were ensured to the participants. The participants were selected via convenience and snowball sampling. The age range was chosen to study young adults, who are more susceptible to social media usage.

Instruments

Three measures were used in this study,

1. **Bergen Social Media Addiction Scale (Andreassen et al., 2016):** was used to measure social media addiction among the participants. It measures the six components of addiction given by Griffith (2005), which are salience, mood modification, withdrawal symptoms, tolerance, conflict and relapse. It is a five-point Likert scale, where 1 indicates "very rarely" and 5 indicates "very often". The final score ranges from 6-30.
2. **Rosenberg Self Esteem Scale** (Rosenberg,1965) is a 10-item, unidimensional self-report instrument that was utilised to assess the participants' self-esteem. It is a 4-point Likert scale with both, positive and negatively worded questions. With a Guttman Scale Coefficient of Reproducibility of 0.92, the scale possesses excellent internal consistency and reliability in this study.

3. **Brief Resilience Scale** (Smith et al., 2008) is a 6-item scale assessing psychological resilience of individuals along a 5-point Likert scale. It analyses the ability to bounce back or recover from stress by having the participants rate the items from "strongly agree" to "strongly disagree" including both, positively and negatively worded questions. The scores range from 6 to 30.

Procedure

An online survey using a Google form was circulated on social media. The survey consisted of 3 psychological scales that assessed the associations between time spent engaging with recommendation algorithms, Social Media Addiction, Self-Esteem and Psychological Resilience.

The results were analysed using Spearman's Correlation and Linear Regression. SPSS software and Microsoft Excel were used to analyse the data. Spearman's correlation was used to assess the strength and direction of the variables.

RESULTS

Table No. 1 Demographic Table

Category	Frequency	Percentages
GENDER		
Female	**99**	**66**
Male	**51**	**34**
EDUCATION		
Higher Secondary (12th grade)	**19**	**12.66**
Undergraduate	**109**	**72.66**
Postgraduate	**22**	**14.66**
EMPLOYMENT		
Employed	**33**	**22**
Unemployed	**117**	**78**
MARITAL STATUS		
Married	**3**	**2**
Unmarried	**147**	**98**

Table No. 2 Spearman's Correlation

An alpha level of 0.01 was selected

			Time (in hours)	**BSMAS Scores**
Spearman's rho	**Time (in hours)**	Correlation Coefficient	1.000	.754**
		Sig. (2-tailed)	.	<.001
		N	150	150
	BSMAS Scores	Correlation Coefficient	.754**	1.000
		Sig. (2-tailed)	<.001	.
		N	150	150
	RSES Scores	Correlation Coefficient	-.262**	-.130
		Sig. (2-tailed)	.001	.113
		N	150	150
	BRS Scores	Correlation Coefficient	-.467**	-.605**
		Sig. (2-tailed)	<.001	<.001
		N	150	150

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

A Spearman's Correlation was conducted to test the relationship between Time (in hours) and the BSMAS Scores. There was a significant positive relationship between Time (in hours) and the BSMAS Scores, r_s (148) =.754, p<.001. Additionally, Time (in hours) showed a significant negative correlation with RSES Scores, r_s (148) =-.262 and p=0.001 and with BRS Scores, r_s (148) =-.467, , p<.001. The correlation between BSMAS Scores and RSES Scores was not significant, r_s (148) =-.130, with p=.113. However, a significant negative correlation was observed between BSMAS Scores and BRS Scores, r_s (148) = -.605, p<.001.

Regression analysis

Table No. 3 Descriptive Statistics

	Mean	Std. Deviation	N
Time (in hours)	2.97	.999	150
BSMAS Scores	19.67	4.815	150
RSES Scores	15.71	1.954	150
BRS Scores	3.5255555556	.74278449731	150

Table No. 4 BSMAS-Time (in hours) model summary

					Change Statistics	
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**R Square Change**	**F Change**
1	783[a]	.613	.610	3.006	.613	234.269

Table No. 5 ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2117.352	1	2117.352	234.269	<.001[b]
	Residual	1337.641	148	9.038		
	Total	3454.993	149			

Dependent variable: BSMAS Scores
Predictors (constant), Time (in hours)

Table No. 6 Coefficients [a]

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
	(Constant)	8.484	.771		11.001	<.001
	Time (in hours)	3.772	.246	.783	15.306	<.001

Dependent variable: BSMAS Scores

A simple linear regression analysis was conducted to evaluate the extent to which time (in hours) could predict BSMAS scores. A significant regression was found, F(1, 148) = 234.27, p < .001. The R^2 was .613, indicating that time (in hours) explains approximately 61.3% of the variance in BSMAS scores.

The regression equation was:
BSMAS Scores = 8.48 + 3.77(Time in hours)

This means, for each one-hour increase in time spent, the predicted BSMAS score increased by approximately 3.77 points.

Table No. 7 RSES-BSMAS Scores model summary

					Change Statistics	
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**R Square Change**	**F Change**
1	.204[a]	.042	.035	1.920	.042	6.442

Table No. 8 ANOVA[a]

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	23.737	1	23.737	6.442	0.12[b]
	Residual	545.357	148	3.685		
	Total	569.093	149			

Dependent variable: RSES Scores
Predictors (constant), BSMAS Scores

Table No. 9 Coefficients[a]

Model		**Unstandardized B**	**Coefficients Std. Error**	**Standardized Coefficients Beta**	**t**	**Sig.**
	(Constant)	17.337	.661		26.216	<.001
	BSMAS Scores	-.083	.033	-.204	-2.538	0.12

Dependent variable: RSES Scores

A simple linear regression was conducted to evaluate the extent to which BSMAS Scores could predict the RSES Scores. A significant regression was found, $F(1, 148) = 6.44$ where $p = .012$. The R^2 was .042, indicating that BSMAS scores explained approximately 4.2% of the variance in RSES scores.

The regression equation was:
RSES Scores = 17.34 - 0.083(BSMAS Scores).

This means for every one point increase in the BSMAS scores, the predicted RSES score decreased by approximately 0.083 points.

Table No. 10 RSES-BRS Scores Model Summary:

					Change Statistics	
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**R Square Change**	**F Change**
1	.104[a]	.011	.004	1.950	.011	1.613

Table No. 11 ANOVA[a]:

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	6.135	1	6.135	1.613	.206[b]
	Residual	562.958	148	3.804		
	Total	569.093	149			

Dependent variable: RSES Scores
Predictors (constant), BRS Scores

Table No. 12 Coefficients [a]:

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
	(Constant)	14.744	.775		19.026	<.001
	BRS Scores	.273	.215	.104	1.270	.206

Dependent variable: RSES Scores

No significant regression was found in the simple linear regression analysis conducted to evaluate the extent to which BRS scores could predict RSES scores, $F(1, 148) = 1.61$ and $p = .206$. The R^2 was .011, indicating that BRS scores explained approximately 1.1% of the variance in RSES scores.

The regression equation was:
RSES Scores = 14.74 + 0.273(BRS Scores).

That is, for each one point increase in BRS scores, the predicted RSES score increased by approximately 0.273 points. However, this relationship was not statistically significant ($p = .206$).

Table No. 13 BSMAS-BRS Scores Model Summary:

					Change Statistics	
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change
1	.616[a]	.379	.375	3.806	.379	90.461

Table No. 14 ANOVA [a]:

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1310.665	1	1310.665	90.461	<.001[b]
	Residual	2144.328	148	14.489		
	Total	3454.993	149			

Dependent variable: BSMAS Scores
Predictors (constant), BRS Scores

Table No. 15 Coefficients [a]:

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	33.751	1.512		22.316	<.001
	BRS Scores	-3.993	.420	-.616	-9.511	<.001

Dependent variable: BSMAS Scores

Lastly, the simple linear regression analysis conducted to evaluate the extent to which BRS scores could predict BSMAS scores, showed a significant regression, $F(1, 148) = 90.46$, and $p < .001$. The R^2 was .379, indicating that BRS scores explained approximately 37.9% of the variance in BSMAS scores.

The regression equation was:
BSMAS Scores = 33.75 - 3.99(BRS Scores).

That is, for each one-point increase in BRS scores, the predicted BSMAS score decreased by approximately 3.99 points.

DISCUSSION

The results indicate that more time spent on social media is strongly associated with higher social media addiction and lower self-esteem. Regression analysis confirms that time significantly predicts BSMAS Scores while the inverse is true for self-esteem. Moreover, resilience negatively predicts social media addiction but has no significant relation with self-esteem.

Lembke (2021), the writer of Dopamine Nation, describes smartphones as the “modern-day hypodermic needle” where social media exploits the brain’s reward system with “cheap dopamine” hits from likes, notifications and infinite scrolling. This dependence interferes with our ability to delay gratification, solve complex problems and handle discomfort; key components of psychological resilience (Waters, 2021). As suggested by previous literature, and the results of our study, increasing psychological resilience can lower the risks of SMA and its negative side effects on self (Bilgin and Taş, 2018; Hou et al., 2017; Hussain and Wegmann, 2021). Further, healthy coping strategies such as meditation, stress management techniques, enhancing interpersonal connections and digital detoxing can help strengthen resilience towards addiction (American Psychological Association, 2020).

As a regulatory measure, combatting the severity of SMA by promoting algorithmic transparency is essential. Social media is increasingly under the scrutiny of various authorities, with efforts being made to hold online platforms accountable for their public actions. For instance, Meta was probed to conduct a Human Rights Internal Assessment (HRIA) over its role in the 2018 Myanmar genocide, along with a further investigation for spreading hate speech in India (Mohanty and Sahu, 2024). Policies regarding social media regulation are evolving, with Australia’s global example of proposing a strict social media ban on children under 16. Similar legislative discussions rolled out in France, the UK, and Norway, setting the precedent for a global shift in how governments confront the growing threats posed by recommendation algorithms, on social media (Ritchie, 2024).

India’s Digital Personal Data Protection Act (2023) mandates verifiable parental consent for minors, and stricter measures to safeguard personal data, especially for minors and individuals with disabilities (Paliwal, 2025). While these regulations are a crucial step towards algorithmic transparency and user protection, stricter implementation, regular audits and global cooperation are necessary to ensure their long-term effectiveness and minimize potential loopholes in AI governance.

CONCLUSION

This study investigated the relationships between time spent on social media (in hours), social media addiction (BSMAS), self-esteem (RSES), and psychological resilience (BRS). The findings revealed that time spent on social media apps significantly predicted social media addiction, with increased time leading to higher BSMAS scores. Additionally, BSMAS scores negatively predicted self-esteem, while BRS scores negatively predicted BSMAS scores, indicating that higher resilience is associated with lower social media addiction. However, no significant relationship was found between BRS scores and RSES scores, suggesting that resilience may not directly influence self-esteem in this context. This study emphasises the need for targeted interventions to reduce social media addiction and promote resilience among young individuals.

Limitations:

The study is based on only 150 respondents, which may not fully represent the entire Indian population. Since data was collected through a survey, responses based on the participants' perceptions and recall may not always be accurate, leading to self-respondent bias. The methodology primarily uses Spearman's Correlation and Linear Regression but does not incorporate advanced statistical techniques which could strengthen the relationship claims. Gender differences might have interfered with the results which have not been taken into account. The standard deviation value for RSES scores (self-esteem) is quite small compared to the mean, thus it can limit the possibility of detecting differences. Further, omitted variable bias exists since factors like income, personal preferences, financial constraints or psychological factors like FOMO have not been considered and are assumed to be constant.

Scope for Future Research:

Future research can explore longitudinal designs to examine causal relationships and consider additional variables, such as mental health outcomes and coping strategies, to provide a more comprehensive understanding of psychological resilience in the digital era. They can focus on the intersection of different forms of persuasive technology and their effects on human psychology.

REFERENCES

Abi-Jaoude, E., Naylor, K. T., & Pignatiello, A. (2020). Smartphones, social media use and youth mental health. *Canadian Medical Association Journal, 192*(6), E136–E141. https://doi.org/10.1503/cmaj.190434

Ali, B. A., Abdulsalam, H. M., Almadani, S., & Manuel, P. (2023). A study of a hybrid Fogg-Hook based social media addictive algorithm from the perspective of Kuwait Society. *Journal of Engineering Research.* https://doi.org/10.1016/j.jer.2023.09.008

American Psychological Association (2020). *Building your resilience.* American Psychological Association. https://www.apa.org/topics/resilience/building-your-resilience

Andreassen, C. S., Billieux, J., Griffiths, M. D., Kuss, D. J., Demetrovics, Z., Mazzoni, E., & Pallesen, S. (2016). Bergen Social Media Addiction Scale (BSMAS) [Database record]. *APA PsycTests.* https://doi.org/10.1037/t74607-000

Andreassen, C., & Pallesen, S. (2014). Social network site addiction - an overview. *Current Pharmaceutical Design, 20*(25), 4053–4061. https://doi.org/10.2174/138161281131 99990616

Atalatti, S., & Pawar, U. (2024). Addictive interfaces. In *Chapman and Hall/CRC eBooks* (pp. 47–66). https://doi.org/10.1201/9781032664828-4

Bilgin, O., & Taş, İ. (2018). Effects of perceived social support and psychological resilience on social media addiction among university students. *Universal Journal of Educational Research, 6*(4), 751–758. https://doi.org/10.13189/ujer.2018.060418

Eyal, N. (2014). *Hooked: How to build habit-forming products.* Penguin Publishing Group. https://books.google.co.in/books?id=dsz5AwAAQBAJ&lpg=PT6&ots=KCGBnzvm RE&lr&pg=PP1#v=onepage&q&f=false

Ferster, C. B., & Skinner, B. F. (1957). Variable ratio. In C. B. Ferster & B. F. Skinner, *Schedules of reinforcement* (pp. 396–419). Appleton-Century-Crofts. https://doi.org /10.1037/10627-007

Fogg, B. (2009). A behavior model for persuasive design. *Persuasive '09: Proceedings of the 4th International Conference on Persuasive Technology.* https://doi.org/10. 1145/1541948.1541999

Garfield, L. (2017, December 23). These tech execs have regrets about the world-changing sites they helped create. *Business Insider.* https://www.businessinsider.com/social-media-affects-society-tech-execs-2017-12#snap-ceo-evan-spiegel-says-social-media-has-encouraged-fake-news-to-spread-3

Haynes, T. (2018). Dopamine, smartphones & you: A battle for your time [BLOG]. *BLOG.* https://unplugged.sunygeneseoenglish.org/wp-content/uploads/sites/31/2019/11/Domamine-PDF.pdf

Hou, X.-L., Wang, H.-Z., Guo, C., Gaskin, J., Rost, D. H., & Wang, J.-L. (2017). Psychological resilience can help combat the effect of stress on problematic social networking site usage. *Science Direct, 109.* https://doi.org/10.1016/j.paid.2016.12.048

Kim, J., & Lee, J. R. (2010). The Facebook paths to happiness: Effects of the number of Facebook friends and self-presentation on subjective well-being. *Cyberpsychology Behavior and Social Networking, 14*(6), 359–364. https://doi.org/10.1089/cyber.2010.0374

Lembke, A. (2021). *Dopamine nation: Finding balance in the age of indulgence.* Penguin.

Malik, P. (2024). The effect of social media usage and self-esteem among adults. *The International Journal of Indian Psychology, 12*(2). https://doi.org/10.25215/1202.072

Mohanty, A., & Sahu, S. (2024). India's advance on AI regulation. https://carnegieendowment.org/research/2024/11/indias-advance-on-ai-regulation?lang=en¢er=india

Moningka, C., & Eminiar, P. R. (2020). The effect of self-comparison in social media on self-esteem. *Atlantis Press.* https://doi.org/10.2991/assehr.k.201125.032

Mujica, A. et al. (2022). ADDICTION BY DESIGN: Some dimensions and challenges of excessive social media use. *Medical Research Archives, 10*(2). https://doi.org/10.18103/mra.v10i2.2677

Orlowski, J. (Director). (2020). *The Social Dilemma* [Film]. Exposure Labs.

Paliwal, A. (2025, January 3). Parental consent must for children's accounts: Centre in draft social media rules. *India Today.* https://www.indiatoday.in/india/story/centre-in-draft-rules-for-data-protection-parental-consent-must-for-children-to-open-social-media-account-2659474-2025-01-03

Pratik Sinha, Sumaiya Shaikh, Pratik Sinha, & Sumaiya Shaikh. (2020, September 17). A techie and a neuroscientist review "The Social Dilemma." *Newslaundry.* https://www.newslaundry.com/2020/09/17/a-techie-and-a-neuroscientist-review-the-social-dilemma

Ritchie, H. (2024). Australian social media ban on under-16s approved by parliament. *BBC News.* https://www.bbc.com/news/articles/c89vjj0lxx9o

Rosenberg, M. (1965). Rosenberg Self-Esteem Scale (RSES) [Database record]. *APA PsycTests.* https://doi.org/10.1037/t01038-000

Sadagheyani, H. E., & Tatari, F. (2020). Investigating the role of social media on mental health. *Mental Health and Social Inclusion, 25*(1), 41–51. https://doi.org/10.1108/mhsi-06-2020-0039

Van Lange, P. A. M., Joireman, J., Parks, C. D., & Van Dijk, E. (2013). The psychology of social dilemmas: A review. In *VU University Amsterdam, Department of Social and Organizational Psychology, Organizational Behavior and Human Decision Processes* (pp. 125–141). https://static1.squarespace.com/static/523f28fce4b0f99c83f055f2/t/52820aeae4b09c1d9bf3bb02/1384254186523/VanLangeEtAl2013OBHDP.pdf

Waters, J. (2021, August 22). Constant craving: How digital media turned us all into dopamine addicts. *The Guardian.* https://www.theguardian.com/global/2021/aug/22/how-digital-media-turned-us-all-into-dopamine-addicts-and-what-we-can-do-to-break-the-cycle

Watson, S. (2024). Dopamine: The pathway to pleasure. *Harvard Health Publishing.* https://www.health.harvard.edu/mind-and-mood/dopamine-the-pathway-to-pleasure

Zaheer Hussain, Z., & Wegmann, E. (2021). Problematic social networking site use and associations with anxiety, attention deficit hyperactivity disorder, and resilience. *Science Direct, 4*, 100125. https://doi.org/10.1016/j.chbr.2021.100125

Zhang, M., & Liu, Y. (2021). A commentary of TikTok recommendation algorithms in MIT Technology Review 2021. *Fundamental Research, 1*(6), 846–847. https://doi.org/10.1016/j.fmre.2021.11.015

Acknowledgment
We would like to express our gratitude to Professor Sarita Jaishankar, our mentor and co-author, for her support and guidance throughout the duration of this research paper, as well as Professor Lorraine Vaz for her continuous motivation and support. We are also thankful to the Department of Psychology for the opportunity to work on this paper and their support in its development. Lastly, we would like to express our gratitude to Ms Mitali Pawaskar for her valuable insights and support in statistical computation, which contributed greatly to our research.

Conflict of Interest
The author(s) declared no conflict of interest.

How to cite this article: Sharma, R. & Bedi, S. (2025). Algorithms, Addiction and Self-Esteem: Psychological Resilience in the Meta Era. *International Journal of Indian Psychology*, *13*(3)*,* 966-978. DIP:18.01.088.20251303, DOI:10.25215/1303.088