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Original Article

Psychiatry/Mental Health Section

Correlation between Work Stress and Social Media Addiction in Patients with Depressive Disorder: A Cross-sectional Study

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ABSTRACT

Introduction: Depression is a leading global health concern, contributing significantly to disability and economic burden worldwide. Work stress and Social Media Addiction (SMA) have been identified as critical factors influencing mental health, often interacting to exacerbate depressive symptoms. However, the combined impact of these variables on patients with depressive disorders remains underexplored.

Aim: To study the relationship between work stress and SMA in patients with depressive disorders.

Materials and Methods: This cross-sectional study was conducted in the Department of Psychiatry at Chettinad Hospital and Research Institute, Chengalpattu, Tamil Nadu, India, among 96 patients aged 18-64 years diagnosed with depressive disorder according to International Classification of Diseases (ICD)-11 criteria. Participants were assessed using the Hamilton Depression Rating Scale (HDRS) for depression, the Tool for Assessment of Work Stress (TAWS-16) for work stress and the Bergen Social Media Addiction Scale (BSMAS) for SMA. Data were analysed using descriptive statistics, Pearson's correlation, and multivariate linear regression, with significance set at p-value <0.05.

Results: Among the participants, 33 individuals (34.37%) exhibited SMA, while 37 individuals (38.54%) reported mild work stress, 38 individuals (39.58%) reported moderate work stress, and 21 individuals (21.87%) reported severe work stress. Significant positive correlations were observed between HDRS and BSMAS scores (r-value=0.571, p-value <0.001), HDRS and TAWS-16 scores (r-value=0.418, p-value <0.001), and BSMAS and TAWS-16 scores (r-value=0.347, p-value <0.001). However, Chi-square analysis revealed no significant association between SMA and work stress categories (p-value=0.437). Regression analysis identified HDRS scores (p-value <0.001) as the only significant predictor of SMA severity.

Conclusion: This study highlights the significant interplay between work stress, SMA and depression severity in patients with depressive disorders. The prevalence of SMA among individuals with depressive disorder was 34.4%. Addressing both occupational stressors and problematic social media use could be pivotal in managing depressive symptoms effectively.

Keywords: Behavioural addiction, Digital addiction, Major depressive disorder, Occupational stress

INTRODUCTION

Depression results from a complex interaction of social, psychological and biological factors contributing to disability worldwide [1]. The global Age Standardised Incidence Rate (ASIR) decreased by 2.35% to 3,588.25 per 100,000 people in 2019 compared to 1990 [2]. As of 2019, approximately 290 million people were affected, marking a 59% increase since 1990 [2]. It accounts for 4.3% of the total global disease burden, with 1.8 million Disability Adjusted Life Years (DALYs) lost annually [2-4]. The economic burden is substantial, with major depressive disorder costing $326 billion annually in high-income countries like the US, primarily due to healthcare expenses and productivity losses [5]. In India, 45.7 million people are affected, contributing 4.7% of the national disease burden and the largest share of mental health DALYs lost [6], with indirect costs significantly straining individuals, families and the healthcare system [7].

Work stress, SMA and depression interact in complex ways, significantly impacting global mental health. Workplace stress, driven by high demands, low control and poor social support, is a key risk factor for depression and anxiety [8,9]. Job insecurity and work-life imbalance contribute to psychological distress, with high psychological job demands doubling the risk of mental health disorders in young adults [9]. Meanwhile, problematic social media use has emerged as a growing behavioural concern, strongly linked to increased depression, anxiety and stress [10,11]. The addictive nature of social media, driven by Fear of Missing Out and constant notifications, reinforces compulsive use and worsens mental health outcomes [12].

The interplay between work stress and SMA further complicates mental health, as individuals under high workplace stress often use social media as a coping mechanism, paradoxically exacerbating their distress. This cycle of dependency heightens the risk of depressive disorders [13,14]. Despite extensive individual research on workplace stress and social media use, there is limited empirical investigation into the combined and interactive effects of these two variables on depression [15-17]. Most existing studies treat these factors in isolation, overlooking how their interdependence may amplify mental health risks. Moreover, there is a scarcity of data from low- and middle-income countries, such as India, where both digital penetration and occupational challenges are rising rapidly. Thus, this study explores the intricate relationship between work stress and SMA in patients with depressive disorders.

MATERIALS AND METHODS

This cross-sectional study was conducted in the Department of Psychiatry at Chettinad Hospital and Research Institute, Chengalpattu, Tamil Nadu, India, from September 2023 to September 2024, after obtaining approval from the Institutional Ethics Committee (IEC) (Ref: IHEC-II/0419/23, dated 11/09/2023).

Inclusion criteria: Individuals who met the ICD-11 diagnostic criteria [18] for depressive disorder, were within the age group of 18 to 64 years, and were willing to provide written informed consent for participation were included in the study.

Exclusion criteria: Participants with history of any co-morbid psychiatric illness, a family history of psychiatric disorders, were unwilling to give written informed consent, or were uncooperative due to the severity of their depressive symptoms, which could hinder accurate data collection or ethical participation were excluded form the study

Sample size calculation: The sample size was calculated to be 96, using the single proportion formula based on a 51.2% prevalence of professional stress [19], at a 95% confidence level and 10% precision, with the assistance of nMaster software (Version 2.0).

Study Procedure

Participants were recruited using convenience sampling. Data collection included demographic details, clinical characteristics, occupational details and details of social media usage, along with assessments using the Hamilton Depression Rating Scale (HAM-D) [20] for depression. The HAM-D or HDRS-17 is a widely used clinician-administered tool consisting of 17 items designed to assess the severity of depression in adults. It has strong validity with high inter-rater reliability and internal consistency. Each item is scored on a 3-point or 5-point scale, yielding a total score ranging from 0 to 52. Scores are interpreted as follows: 0-7 (no depression), 8-16 (mild), 17–23 (moderate), and ≥24 (severe depression) [21].

The TAWS-16 [22-25] is a validated instrument designed to identify work-related stress among employees, particularly in the Indian occupational context. It consists of 32 items divided into two sections: Section A includes 16 items that assess various work-related stressors and stress levels, while Section B comprises 16 items that evaluate symptoms suggestive of stress. There are 2 steps in Section A. The first step asks about exposure to a work stressor and is scored from 0 to 2 (0: no, not at all; 1: yes, to some extent; 2: yes, to a greater extent). The second step assesses how individuals cope with the stressor and is scored from 1 to 4 (1: no, not at all; 2: yes, on few occasions, but I manage; 3: yes, often and difficult to manage; 4: yes, very frequently and excessively stressed, difficult to manage). The cut-off is based on the minimum affirmative score possible, which is 48. Hence, all individuals scoring 48 and above are deemed to have experienced work stress. Scoring of Section A is interpreted as follows: 0-47 (no harmful work stress), 48+ (harmful work stress reported), 48-59 (mild work stress), 60-73 (moderate work stress), and more than 73 (severe work stress). Section B consists of 16 items about symptoms of work stress, rated on a scale of 0 to 3 (0: never; 1: yes, occasionally; 2: yes, repeatedly; 3: yes, regularly). Scoring of Section B is as follows: 0-15 (no experience of symptoms of work stress), 16-29 (mild experience of symptoms of work stress), 30-36 (moderate experience of symptoms of work stress), and more than 36 (severe symptoms of work stress). The tool has demonstrated acceptable scores for face validity, as well as acceptable quantitative indices for content, construct and criterion validity. It also has clear and meaningful parameters for reliability assessments and is satisfactory with high internal consistency.

The BSMAS [26] is a six-item self-report measure assessing the risk of SMA, grounded in the core components of addiction. It has been validated across various populations and cultures. Each item is rated from 1 (very rarely) to 5 (very often), with a total score range of 6 to 30, where higher scores indicate more problematic use. A score of 24 and above is considered indicative of SMA [25].

STATISTICAL ANALYSIS

Data were collected using structured questionnaires, entered into Microsoft Excel and securely stored in a protected folder. The dataset was cleaned in Excel and subsequently imported into Jamovi Solid Version 2.3.28 for analysis. Descriptive statistics were applied to summarise socio-demographic and clinical variables. Continuous data were expressed as means and standard deviations, while categorical data were presented as frequencies and percentages. The normality of data distribution was assessed using QQ plots.

Pearson's correlation coefficient was utilised to examine relationships between HAM-D, BSMAS and TAWS-16 scores. To identify predictors of BSMAS scores, multivariate linear regression analysis was conducted, considering socio-demographic factors and scores from HAM-D and TAWS-16 as independent variables. All statistical analyses were performed using Jamovi (Version 2.3.28), with a p-value of <0.05 considered statistically significant.

RESULTS

[Table/Fig-1] shows that the majority of the 96 participants belonged to the 51-64 years age group 38 (39.6%), were male 55 (57.3%), and identified as Hindu 79 (82.3%). Most of them had higher secondary education 19 (19.8%) or graduate-level education 21 (21.9%) and lived in nuclear families 82 (85.4%). Participants were from urban 42 (43.8%), rural 41 (42.7%), and semiurban 13 (13.5%) areas, with nearly half classified as upper middle class 45 (46.9%), followed by upper class 42 (43.8%) and a smaller proportion in the middle-income group 9 (9.4%). Job characteristics [Table/Fig-2] revealed that over half were semiskilled workers 52 (54.2%), while 23 individuals (24.0%) worked night

Characteristics	Count (%)
Age (in years)	
18-30	19 (19.8)
31-40	16 (16.7)
41-50	23 (24.0)
51-64	38 (39.6)
Gender	
Male	55 (57.3)
Female	41 (42.7)
Religion	
Hindu	79 (82.3)
Christian	13 (13.5)
Muslim	4 (4.2)
Educational qualification	
No formal schooling	13 (13.5)
Elementary school	14 (14.6)
High school	16 (16.7)
Higher secondary school	19 (19.8)
Graduate	21 (21.9)
Postgraduate	13 (13.5)
Type of family	
Nuclear	82 (85.4)
Joint	14 (14.6)
Residence	
Urban	42 (43.8)
Rural	41 (42.7)
Semiurban	13 (13.5)
Socio-economic status	
Upper	42 (43.8)
Upper middle	45 (46.9)
Middle	9 (9.4)
Marital status	
Married	76 (79.1)
Never married	17 (17.7)
Separated	3 (3.1)

[Table/Fig-1]: Socio-demographic of the study population (N=96).

Job characteristics	n (%)
Classification of job (N=96)	
Skilled	33 (34.3)
Semiskilled	52 (54.2)
Unskilled	11 (11.5)
Recent change of job (N=96)	
Yes	11 (11.5)
No	85 (88.5)
Total no. of job changes (N=11)	
1	11 (100.0)
Night shift worker (N=96)	
Yes	23 (24.0)
No	73 (76.0)
Work hours (N=23)	
7	1 (4.3)
8	8 (34.8)
9	4 (17.4)
10	5 (21.7)
12	5 (21.7)
Duration of current job (in years) (mean±SD)	16.85±11.97

[Table/Fig-2]: Job characteristics of the study population N=96).

shifts, primarily for 8-12 hours. A small proportion (n=11, 11.5%) had recently changed jobs.

[Table/Fig-3] shows that the average age of onset of illness was 43.135±13.18 years (mean±SD). The average total duration of illness was 14.427±12.85 months, and the average duration of the current episode was 3.307±2.29 months. Out of 96 patients, 21 individuals (21.9%) had a history of prior hospitalisations. Additionally, 45.8% of individuals had no previous depressive episodes, 40.7% had experienced one depressive episode in the past and 13.5% had experienced two or more (≥2) episodes.

Variable		Mean±SD	Median	Min	Max	95% CI Upper	95% CI Lower
Age of onset of illness (in years)		43.135±13.18	43.5	18	64	43.77	40.50
Total duration of illness (in months)		14.427±12.85	10.75	0.5	54	17.03	11.82
Total duration of current episode (in months)		3.307±2.29	2.75	0.5	10.5	3.78	2.84
Variables		n (%)					
Total number of previous episodes	0	44 (45.8)					
	1	39 (40.7)					
	≥2	13 (13.5)					
Previous hospitalisation	0	75 (78.1)					
	1	21 (21.9)					

[Table/Fig-3]: Distribution of severity of current and past depressive episode in the study population (N=96).

[Table/Fig-4] highlights the impact of social media usage on daily life, with participants averaging 3.4 hours per day, leading to reduced sleep (2 hours), work time (1.5 hours), and family time (1.1 hours). Additionally, participants spent 0.4±0.24 hours thinking about social media, and the median number of attempts to avoid social engagements for social media use was 1 (IQR: 1-2), reflecting a shift towards online priorities and highlighting its pervasive influence on emotional wellbeing and daily life. WhatsApp was the most used app 96 (100%), followed by YouTube 81 (84.4%), Facebook 50 (52.1%), and Instagram 39 (40.6%). Emotional effects included sadness from reduced social media time 14 (14.6%) and frustration over slow networks 70 (73%). Attempts to cut usage

Characteristics	Mean±SD
Duration of smart phone usage (in hours)	3.4±0.74
Duration of sleep affected (in hours)	2±0.47
Duration of work time affected (in hours)	1.5±0.43
Amount of family time affected (in hours)	1.1±0.5
Amount of decrease in time on other hobbies (in minutes)	0.6±0.23
Amount of time thinking about what happened on social media recently (in hours)	0.4±0.24
Number of times tried quitting social engagements in order to be on social media*	1 (1-2)

[Table/Fig-4]: Impact of social media usage in various aspects of daily life in the study population (N=96).
*Median (IQR)

failed for 21 (21.87%), while 10 (10.4%) reported reduced physical activity, and 4 (4.2%) admitted to making excuses to use social media at work. These findings highlight its pervasive influence on daily life [Table/Fig-5].

Characteristics	Count (%)
Frequently used apps	
WhatsApp	96 (100)
YouTube	81 (84.4)
Facebook	50 (52.1)
Instagram	39 (40.6)
Felt sad if spent less time on social media	14 (14.6)
Tried to cut down on social media without success	21 (21.87)
Felt disturbed if social media network is slow or unavailable	70 (73)
Felt physically less active due to use of social media	10 (10.4)
Do you search for excuses to use social media while working	4 (4.2)

[Table/Fig-5]: Social media usage features in the study population (N=96).

Based on the HDRS scores, 41 participants (42.71%) had mild depression, 42 (43.75%) had moderate depression, and 13 (13.54%) had severe depression. The HDRS scores had a mean of 17.5±5.4, ranging from 9 to 29 [Table/Fig-6]. SMA was present in 33 (34.37%) of participants, while 63 (65.63%) did not have SMA. The BSMAS scores showed a mean of 18.94±7.14, with a range of 6 to 30 [Table/Fig-7]. Among the participants, 37 (38.54%) had mild work stress, 38 (39.58%) had moderate work stress, and 21 (21.87%) experienced severe work stress [Table/Fig-8]. The Total Work Stress Score (TAWS-16 Part A) had a mean of 63.07±10.43, ranging from 40 to 83, while the Stress Symptoms Score (TAWS-16 Part B) exhibited a mean of 27.0±4.0, with a range of 20 to 36.

Severity of current episode (HDRS score)	n (%)			
Mild	41 (42.71)			
Moderate	42 (43.75)			
Severe	13 (13.54)			
	Mean±SD	**Median**	**Min**	**Max**
Total HDRS score	17.5±5.44	18	9	29

[Table/Fig-6]: Severity of depression-current episode in the study population (N=96).

Social Media Addiction (SMA)	n (%)			
Absent	63 (65.63)			
Present	33 (34.3)			
	Mean±SD	**Median**	**Min**	**Max**
Total BSMAS score	18.94±7.14	20	6	30

[Table/Fig-7]: Social Media Addiction (SMA) in the study population (N=96).

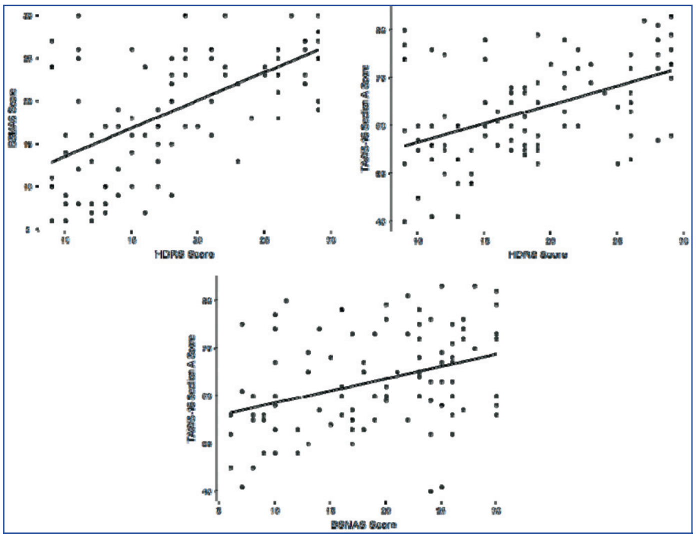
The correlation matrix in [Table/Fig-9] and the scatter plots in [Table/Fig-10] demonstrate the relationships between HDRS, BSMAS and work stress (TAWS-16 Section A) scores. A significant positive

Work stress	n (%)			
Mild	37 (38.54)			
Moderate	38 (39.58)			
Severe	21 (21.87)			
	Mean±SD	Median	Min	Max
Total TAWS-16A score	63.072±10.43	61.5	40	83
Total TAWS-16B score	27.00±4.00	27	20	36

[Table/Fig-8]: Occupational stress in the study population (N=96).

		HDRS score	BSMAS score
BSMAS Score	Pearson's r	0.571	
	df	94	
	p-value	<0.001	
TAWS 16 Section A score	Pearson's r	0.418	0.347
	df	94	94
	p-value	<0.001	<0.001

[Table/Fig-9]: Correlation matrix between Severity of Depression, Social Media Addiction (SMA) and Work stress scores in the study population (N=96).
*p<0.05 is considered statistically significant



[Table/Fig-10]: Scatter plot between HRDS, BSMAS, and Work stress scores in the study population (N=96).

correlation was observed between HDRS and BSMAS scores (r-value=0.571, p-value<0.001). Similarly, HDRS scores showed a significant positive correlation with TAWS-16 Section A scores (r-value=0.418, p-value<0.001). Additionally, BSMAS scores were positively correlated with TAWS-16 Section A scores (r-value=0.347, p-value<0.001). These findings indicate that higher depressive symptoms, SMA and work stress are interrelated.

SMA was significantly associated with higher depressive symptom severity as measured by HDRS scores (χ^2 (2)=7.01, p-value=0.03). Among individuals with SMA, the majority exhibited moderate depressive symptoms (n=19, 57.6%), followed by mild (n=8, 24.2%) and severe symptoms (n=6, 18.2%). In contrast, no significant relationship was observed between SMA and work stress levels (χ^2 (3)=1.66, p-value=0.437), indicating that work stress may not play a major role in SMA [Table/Fig-11]. The multivariate regression analysis [Table/Fig-12] showed that higher HDRS scores significantly predicted greater SMA severity, while work-related stressors or stress levels had no significant associations with BSMAS scores. The model demonstrated a good fit, with no issues of autocorrelation in the residuals.

In summary, this study found a significant positive correlation between HDRS, BSMAS and work stress (TAWS-16 Section A) scores (r-value=0.571, p-value<0.001; r-value=0.347, p-value<0.001). However, Chi-square analysis showed no significant association between SMA and work stress categories (p-value=0.437),

	Social Media Addiction (SMA)		Chi-square	
Score categories	Present	Absent	χ^2	p-value
HDRS				
Mild	8 (24.2%)	33 (52.4%)	7.01	0.03*
Moderate	19 (57.6%)	23 (36.5%)		
Severe	6 (18.2%)	7 (11.1%)		
TAWS-16 (Work stress)				
Mild	10 (30.3%)	27 (42.9%)	1.66	0.437
Moderate	14 (42.4%)	24 (38.1%)		
Severe	9 (27.3%)	12 (19%)		

[Table/Fig-11]: Association of Social Media Addiction (SMA) with Depression Severity and Work Stress in the study population (N=96).
*p<0.05 is considered statistically significant

Predictor	Estimate	95% CI Lower	95% CI Upper	p-value
HDRS Score	0.71	0.45	0.98	<0.001*
TAWS-16 Section A score	0.06	-0.08	0.21	0.375
Age category				
18-30 vs. 31-40	-2.43	-7.63	2.76	0.354
41-50 vs. 31-40	1.60	-2.63	5.83	0.454
51-64 vs. 31-40	0.31	-3.67	4.30	0.876
Gender				
Male vs. Female	0.86	-1.86	3.58	0.529
Marital status				
Never married vs. married	1.26	-3.37	5.89	0.590
Separated vs. married	-0.71	-8.12	6.69	0.849
Type of family				
Nuclear vs. joint	1.60	-2.29	5.50	0.415
Residence				
Rural vs. semiurban	2.54	-1.67	6.76	0.233
Urban vs. semiurban	2.04	-2.10	6.17	0.330
Socioeconomic status				
Upper vs. middle	1.52	-3.76	6.80	0.569
Upper middle vs. middle	1.54	-3.56	6.64	0.550
Educational qualification				
Elementary school vs no formal schooling	4.51	-0.15	9.16	0.057
Graduate vs no formal schooling	4.03	-0.75	8.81	0.097
High school vs no formal schooling	1.06	-7.40	9.53	0.803
Higher secondary school vs no formal schooling	4.74	-8.80	18.28	0.488
Post-graduate vs no formal schooling	4.29	-0.70	9.27	0.091

[Table/Fig-12]: Multivariate analysis of BSMAS score in the study population (N=96).
*p<0.05 is considered statistically significant.

and multivariate regression confirmed that TAWS-16 was not a significant predictor (p-value=0.375). HDRS scores were the only significant predictor of BSMAS scores (p-value <0.001), with the model explaining 32% of variability (adjusted R^2=0.32).

DISCUSSION

This study investigated the relationship between work stress, SMA and depressive symptoms in individuals diagnosed with depressive disorder, focusing on the prevalence and predictors of SMA. Among the participants, 34.37% exhibited SMA, highlighting its significant presence in a clinical population. Depression severity, as measured by HDRS, emerged as the sole significant predictor of SMA, underscoring its central role in driving problematic digital behaviours. Interestingly, no significant association was observed between work stress categories and SMA, suggesting that these variables interact through more complex or indirect pathways. Participants also reported behavioural disruptions, including reduced sleep, family time and productivity, emphasising the broader impact of SMA on daily life. The observed prevalence of SMA (34.37%) aligns with findings from studies conducted in non clinical populations but remains lower compared to other high-risk groups. Zulfiqar S et al., reported a prevalence of 58.8% among nursing students in Karachi, reflecting their heightened vulnerability due to professional and academic pressures [27]. Similarly, Zaw CC and Azenal NA, observed a prevalence of 37% among Malaysian nursing students, a figure that aligns closely with these findings and underscores the impact of occupational stressors unique to healthcare trainees [28].

Among adolescents, Victor SA et al., found a much higher prevalence of 72%, likely driven by developmental vulnerabilities and excessive engagement with social media platforms, as also noted by Sommantico M et al., [29,30]. These variations in prevalence underscore the importance of considering demographic and contextual factors, as well as methodological differences, when interpreting rates of SMA. Methodological differences across studies may partly explain the discrepancies in prevalence rates. While this study employed the BSMAS, which assesses addiction severity broadly, Zulfiqar S et al., used the social networking addiction scale, which incorporates platform-specific behaviours such as time spent and frequency of use [27]. Similarly, Sommantico M et al., found that work stress, compounded by Fear of Missing Out (FoMO), contributed to problematic social media use among young adults [30]. These contrasting findings may be explained by differences in the instruments used to assess work-related stress. Similarly, Priyadarshini C et al., identified high levels of digital dependency in employees, although specific prevalence rates were not reported [31]. These methodological variations, combined with differences in population characteristics, may influence the observed prevalence and highlight the need for standardised assessment tools in future research.

The absence of a direct association between work stress and SMA in this study diverges from findings by Gomez LM and Perez JR, who reported that workplace stress significantly predicted digital dependency in government employees [32]. The present study employed the multidimensional TAWS-16 scale, whereas other studies have often utilised simpler or more targeted occupational stress measures. Additionally, focusing on individuals with depressive disorder may underscore depression as the predominant factor influencing SMA, thereby diminishing the relative impact of work stress in this context.

Behavioural disruptions reported by the participants in this research align with prior studies that emphasise the negative consequences of SMA. Zivnuska S et al., noted significant impacts on work–family balance, increased burnout and reduced job performance in employees with high social media use [33]. Similarly, Priyadarshini et al., highlighted disruptions to sleep, productivity and workplace relationships among employees, while Huang PC et al., observed that SMA in adolescents contributed to reduced physical activity and heightened psychological distress [31,34]. Unlike these studies, which focused on non clinical populations, the present findings add to the literature by contextualising these behavioural disruptions within a clinical population, offering unique insights into how digital dependency compounds mental health challenges.

Overall, this study contributes to the growing body of literature emphasising the interplay between mental health, digital behaviours and occupational stress. Examining these dynamics within a clinical population offers a more nuanced understanding of how depression contributes to SMA, while also identifying potential areas for targeted intervention.

Limitation(s)

The study had several limitations. Its cross-sectional design prevents the establishment of causal relationships between variables. Additionally, the use of convenience sampling may have introduced selection bias, potentially affecting the generalisability of the findings. Furthermore, the reliance on self-reported measures raises the possibility of social desirability and recall biases. To address these issues, future research should employ longitudinal designs to better assess causality and build upon the current findings.

CONCLUSION(S)

This study highlights the high prevalence of SMA (34.37%) among individuals with depressive disorder and its strong association with depression severity, while the absence of a direct link with work stress suggests complex underlying interactions. Behavioural disruptions from excessive social media use, including reduced sleep, family time and productivity, underscore its broader societal impact. These findings emphasise the need for targeted mental health interventions, promoting digital literacy, mindful social media use and healthier coping strategies, particularly in vulnerable populations. Employers should recognise the indirect role of occupational stress in digital dependency and implement policies that support employee well-being. Future research should explore these dynamics longitudinally, conduct platform-specific analyses and assess mediating factors such as personality traits and coping mechanisms to develop effective interventions.

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