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ORIGINAL RESEARCH

Social Media Addiction and Sleep Quality Among High School Graduates in Bangladesh: A Network Perspective

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Objective: Social media has been implicated in curtailing the quality and quantity of sleep. This study applied a network analysis approach to explore associations between social media addiction (SMA) and sleep quality among prospective university students, to identify central and bridge symptoms and compare networks by gender.

Methods: A cross-sectional survey was conducted among 1139 Bangladeshi university entrance examinees in February 2025 using a convenience sampling technique. Participants completed the Bergen Social Media Addiction Scale and the Pittsburgh Sleep Quality Index. A Gaussian Graphical Model was estimated using the Extended Bayesian Information Criterion Graphical Lasso (EBICglasso). Network centrality, bridge centrality, stability, and accuracy were evaluated. Network comparison tests (NCT) were performed across genders. All analyses were conducted using R (version 4.4.1) and SPSS (version 27).

Results: Strong intra-domain connections emerged within both SMA (Conflict–Relapse; Tolerance–Withdrawal) and sleep (Sleep Quality–Latency; Disturbance–Medication Use). Cross-domain associations included Relapse–Daytime Dysfunction and Mood Modification–Sleep Efficiency. Bridge centrality identified Daytime dysfunction, Mood modification, and sleep latency as prominent connectors. Males reported higher SMA scores, whereas females exhibited poorer sleep quality. The NCT indicated significant gender-based structural differences (M = 0.203, p = 0.013), though global strength remained similar.

Conclusion: Findings highlight symptom-level associations between SMA and sleep quality and suggest gender-sensitive targets for behavioral intervention among adolescents and young adults.

Keywords: social media addiction, sleep quality, network analysis, bridge centrality, youth, gender differences

Introduction

The pervasive use of social media has become a defining and ubiquitous characteristic of modern society, with platforms such as Facebook, Instagram, TikTok, and Twitter being deeply integrated into the daily lives of individuals worldwide. Although social media provides opportunities for connectivity and information, excessive use has been consistently linked with mental health issues and sleep disturbances.[1,2] One of the emerging areas of concern is the potential relationship between problematic social media use, often conceptualized as social media addiction (SMA), and sleep disturbances. This study focuses on sleep quality in relation to excessive use of social media.[2]

Sleep is a vital physiological process essential for cognitive, emotional, and physical functioning and well-being. Poor sleep quality has been associated with a large array of negative health outcomes, including mood disorders, cognitive impairments, cardiovascular conditions, type 2 diabetes mellitus, and decreased work or learning productivity.[3] In recent years, the intersection between digital behavior and sleep has gained scholarly attention, particularly among adolescents and young adults, who are the most active users of social media.[4] The ubiquitous nature of smartphones and round-the-

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clock access to social media platforms has led to increased screen time before bedtime, night-time awakenings, and delayed sleep onset, all of which contribute to insufficient sleep as well as diminished sleep quality.[4,5]

Social media addiction is characterized by excessive preoccupation with social media, a compulsive urge to engage with it, and sustained use that interferes with other important aspects of daily life.[6] This behavioral pattern closely resembles behavioral addiction and may result in emotional dysregulation, withdrawal symptoms, and disrupted circadian rhythms, which are key contributors to poor sleep outcomes.[7] Although numerous studies have reported associations between SMA and sleep disturbances, most have employed variable-centered approaches such as regression analysis or structural equation modeling.[2,8] Unlike variable-centered approaches, network analysis does not assume a latent construct but treats symptoms as interacting components. This allows researchers to identify central and bridge symptoms that sustain comorbidities and serve as potential intervention targets.

Network analysis has emerged as a powerful tool in psychopathology research, offering an innovative means to visualize and quantify the interrelations among symptoms within and across mental health domains.[9] Rather than viewing symptoms as mere indicators of an underlying disorder, the network perspective conceptualizes them as autonomous and interactive elements of a system. In this framework, symptoms can directly reinforce one another; and identifying central and bridge nodes becomes key to understanding the mechanisms of comorbidity and facilitate the design of targeted interventions.[10,11]

Despite the growing application of network models in mental health research, there is limited empirical work that applies this approach to understand the bidirectional dynamics between social media addiction and sleep.[12–14] Recent network-based studies have examined the structure of internet addiction and related constructs, including insomnia and adolescent well-being, demonstrating complex symptom-level interconnections.[12–14] However, these studies primarily focused on general internet use or mental health symptoms and did not integrate multidimensional sleep quality indicators with social media-specific addiction components. Furthermore, gender-based network comparisons, critical for understanding differential psychosocial processes, remain underexplored in this domain. The present study therefore extends existing research by jointly modeling SMA and sleep quality within a unified network, enabling the identification of both intra- and cross-domain bridge symptoms and gender-specific structural patterns.

In the Bangladeshi context, previous studies have consistently reported a high prevalence of poor sleep quality among adolescents and young adults. For instance, the rate of poor sleep quality among university students ranged from 58.4%[15] to 67.57%.[16] Among university entrance test-takers, 62.9% had abnormal sleep duration (<7 hours/night or >9 hours per), and 25.5% experienced insomnia problems.[17] Prior research in Bangladesh have also demonstrated a positive association between SMA and poor sleep quality.[16] These findings highlight that sleep-related problems and excessive social media use are pressing public health concerns among Bangladeshi youth.

However, the existing studies often fail to integrate key domains from both constructs or to assess potential gender-based differences in symptom interactions. Given the gender-specific trends observed in both SMA (with females often showing higher emotional engagement with social platforms) and sleep disorders (with males frequently underreporting symptoms), examining the structural distinctions between male and female symptom networks may offer valuable insights.[18,19]

The present study aimed to explore the associations between social media addiction and sleep quality using a network analytic framework. Specifically, we sought to (i) estimate the structure of a network comprising SMA symptoms and components of sleep quality, (ii) identify the most central and influential nodes within the network, (iii) examine bridge symptoms that link the two domains, (iv) assess the stability and accuracy of the network, and (v) compare network structures across gender. By adopting this approach, we aimed to advance a nuanced understanding of how problematic social media use interacts with sleep-related impairments, thereby informing more targeted and symptom-specific intervention strategies.

Methods

Study Procedure and Participants

A cross-sectional survey design was employed, as it enables the efficient assessment of relationships between multiple variables within a defined population at a single point in time. This design is particularly suitable for exploratory studies investigating behavioral and psychological associations, such as between social media addiction and sleep quality, without requiring long-term follow-up.[20,21]

The study was conducted among recent high school graduates in Bangladesh, a group undergoing a transitional phase from adolescence to early adulthood, characterized by heightened academic stress, irregular sleep patterns, and frequent social media engagement.[17,22] These characteristics make this population especially relevant for exploring the interplay between digital behaviors and sleep health.

Data were collected in February 2025 at a large public university in Dhaka, where students from across the country had gathered to sit for the university entrance examination. A semi-structured questionnaire was administered in person using a non-probability convenience sampling method. This method was chosen due to the accessibility and geographic clustering of participants, which made it feasible to collect data from a large, diverse cohort within limited time and logistical constraints. Convenience sampling is widely used in behavioral health research when target populations are concentrated in specific settings and the study aims to explore associations rather than establish causality.[23]

Inclusion criteria were: recent high school graduates who appeared for the university entrance examination and were willing to provide informed consent. Exclusion criteria included incomplete responses on the main study variables (BSMAS or PSQI).

Of the 1163 students who completed the questionnaire, 24 cases with missing data on key variables (social media addiction and sleep quality) were excluded through listwise deletion, resulting in a final analytic sample of 1139 participants.

Measures

Social Media Addiction

Social media addiction was assessed using the Bergen Social Media Addiction Scale (BSMAS).[24] The BSMAS comprises six items representing core addiction components: salience (SM1), mood modification (SM2), tolerance (SM3), withdrawal (SM4), conflict (SM5), and relapse (SM6). Each item is rated on a 5-point Likert scale ranging from 1 (very rarely) to 5 (very often), with higher scores indicating a greater degree of social media addiction. The Bangla version of BSMAS was used in the study, which showed good psychometric properties.[25] The Cronbach's alpha was 0.79 in the study.

Sleep Quality

Sleep quality was explored using the Pittsburgh Sleep Quality Index (PSQI),[26] a widely used self-report questionnaire designed to assess sleep over the past month. The PSQI consists of seven components: subjective sleep quality (QL), sleep latency (LC), sleep duration (DN), habitual sleep efficiency (SE), sleep disturbances (DS), use of sleeping medication (MD), and daytime dysfunction (DD). Each component is scored from 0 to 3, with higher scores indicating greater sleep difficulties.[26] The Bangla version of the PSQI was used in the study, which showed good psychometric properties.[27] The Cronbach's alpha was 0.79 in the study.

Ethical Considerations

This study adhered to the ethical principles of the Declaration of Helsinki (1975; revised 2013) and was approved by the CHINTA Research Bangladesh Ethics Committee (Ref: chinta/2025/02(5)). Participants were recent high school graduates sitting for university entrance examinations. The majority were aged 18 years or older; however, 9 participants were aged 16 and 29 participants were aged 17. All participants provided written informed consent after being briefed on the study's purpose, confidentiality of responses, voluntary participation, and the right to withdraw at any time. For participants under 18 years, additional parental/guardian consent was obtained in accordance with ethical requirements. Data were anonymized and stored securely. No monetary or academic incentives were offered for participation.

Statistical Analysis

All statistical analyses were conducted in R (version 4.4.1) and IBM Statistical Package for Social Science (SPSS) version 27. Descriptive statistics (mean, percentages) were calculated to summarize participants characteristics. Independent sample *t*-tests were performed to examine gender differences in SMA and PSQI. Effect sizes were calculated and interpreted as Cohen's *d*, where values of 0.2, 0.5, and 0.8 represent small, medium, and large effect sizes, respectively. Network analysis was employed to explore the complex relationships between symptoms of SMA and components of sleep quality. This analytical approach estimates partial correlations between variables, meaning each edge reflects an association after statistically controlling for all other nodes in the network. Thus, potential confounding effects among the included variables are inherently accounted for. Conceptual definitions of all BSMAS and PSQI items are provided in Appendix Table A1.

Data Preparation

SPSS data files were imported using the *haven* package. Thirteen variables—six SMA items (SM1-SM6) and seven sleep quality indicators (SE, QL, DN, LC, DS, MD, DD), were selected and extracted using the *dplyr* package. Missing values were removed through listwise deletion using the *na.omit()* function to ensure complete-case analysis.

Network Estimation

The network structure was estimated using the Extended Bayesian Information Criterion Graphical Lasso (*EBICglasso*) method via the *estimateNetwork()* function from the *bootnet* package. This method was chosen for its robustness in estimating sparse networks, especially for psychological data. A tuning parameter ($\gamma = 0.5$) was applied to balance model sparsity and accuracy, as recommended in prior methodological literature. The analysis was conducted at the item/component level to capture specific interactions between individual SMA symptoms and sleep components, providing greater resolution than scale-level associations and allowing identification of the most influential (central or bridge) symptoms. The resulting weighted, undirected network was visualized using the *qgraph* package with nodes representing individual variables and edges indicating regularized partial correlations.[28] All analyses were conducted using default regularization settings to ensure replicability.

Centrality and Bridge Centrality

Centrality indices including strength, closeness, and betweenness were computed using the *centrality()* function to identify the most influential nodes in the network. Bridge centrality measures were computed with the *networktools* package to identify key nodes that serve as connectors between the SMA and sleep quality communities. Metrics such as bridge strength, bridge closeness, bridge betweenness, and bridge expected influence were used to quantify the bridging roles of specific symptoms.

Network Accuracy and Stability

To evaluate the robustness of the network, both edge weight accuracy and centrality stability were assessed. Edge accuracy was tested using nonparametric bootstrapping (1000 samples), and confidence intervals for edge weights were visualized. Centrality stability was evaluated through a case-dropping bootstrap approach implemented in the *bootnet* package. The correlation stability coefficient (CS-coefficient) was calculated to determine how robust centrality indices were to sub-sampling. For the CS coefficient, values greater than or equal to 0.25 indicated acceptable stability, and values greater than or equal to 0.5 indicated good stability.[29] As there is no universally fixed sample size requirement for psychological networks, recent methodological guidelines emphasize evaluating stability indices rather than applying universal rules.[10] Nonetheless, samples exceeding 500 participants are generally considered adequate for reliable estimation in networks of comparable size.[10] We therefore assessed edge-weight accuracy and centrality stability using bootstrapped procedures.

Network Comparison Test (NCT)

To compare network structures between male and female participants, a Network Comparison Test (NCT) was performed using the *NetworkComparisonTest* package.[30] The test assessed (i) network structure invariance (using M-statistics), (ii) global strength invariance (using S-statistics), and (iii) edge and centrality invariance for individual nodes and connections. A permutation-based approach with 1000 iterations was used to determine significance.

Results

Participants Characteristics

Participants' mean age was 19.15 ± 1.06 years. Among the participants, 50.6% were male (n = 576), had average SMA score of 13.52 ± 6.34, and PSQI global score of 7.40 ± 3.27, indicating generally poor sleep quality (Table 1).

Gender Differences in Social Media Addiction and Sleep Quality

Gender-based comparisons revealed significant differences in both SMA and PSQI scores. Male participants (Mean ± SD = 14.09 ± 6.25) reported significantly higher SMA scores than females (Mean ± SD = 12.94 ± 6.40), t = 3.08, p =0.002, Cohen's d = 0.18, indicating a small effect size. Conversely, female participants (Mean ± SD = 7.94 ± 3.41) had significantly higher PSQI global scores than males (Mean ± SD = 6.88 ± 3.06), t = –5.52, p <0.001, Cohen's d = 0.33, also reflecting a small-to-moderate effect size (Table 2). These findings suggest that males exhibited slightly greater tendencies toward social media addiction, whereas females reported poorer sleep quality.

Network Structure

The network structure of SMA and sleep quality is presented in Figure 1. The network structure illustrates the conditional dependencies among 13 variables representing SMA and sleep quality components. Nodes are color-coded by domain—blue for SMA symptoms and orange for PSQI components. The thickness and color intensity of the edges represent the strength of the regularized partial correlations, with thicker, darker green lines indicating stronger associations.

The network reveals key conditional dependencies among SMA symptoms and sleep quality components. In the SMA subnetwork, strong associations were found between SM5 (Conflict) and SM6 (Relapse), as well as between SM3 (Tolerance) and SM4 (Withdrawal), indicating tightly connected patterns of behavioral addiction. In the sleep quality

Table 1 Participant Characteristics (N = 1139)

Variable	Category / Unit	n (%) / Mean ± SD
Age (years)		19.15 ± 1.06
Gender	Male	576 (50.6%)
	Female	563 (49.4%)
Social Media Addiction (BSMAS total)		13.52 ± 6.34
Sleep Quality (PSQI global score)		7.40 ± 3.27

Table 2 Gender Differences in Social Media Addiction and Sleep Quality (N = 1139)

Variable	Gender	Mean ± SD	t (*df* = 1137)	p-value	Cohen's d
Social Media Addiction (BSMAS total)	Male (n = 576)	14.09 ± 6.25	3.08	0.002	0.18
	Female (n = 563)	12.94 ± 6.40			
Sleep Quality (PSQI global score)	Male (n = 576)	6.88 ± 3.06	–5.52	<0.001	0.33
	Female (n = 563)	7.94 ± 3.41			

Note: Cohen's d values of 0.2, 0.5, and 0.8 represent small, medium, and large effect sizes, respectively.
Abbreviations: BSMAS, Bergen Social Media Addiction Scale; PSQI, Pittsburgh Sleep Quality Index.

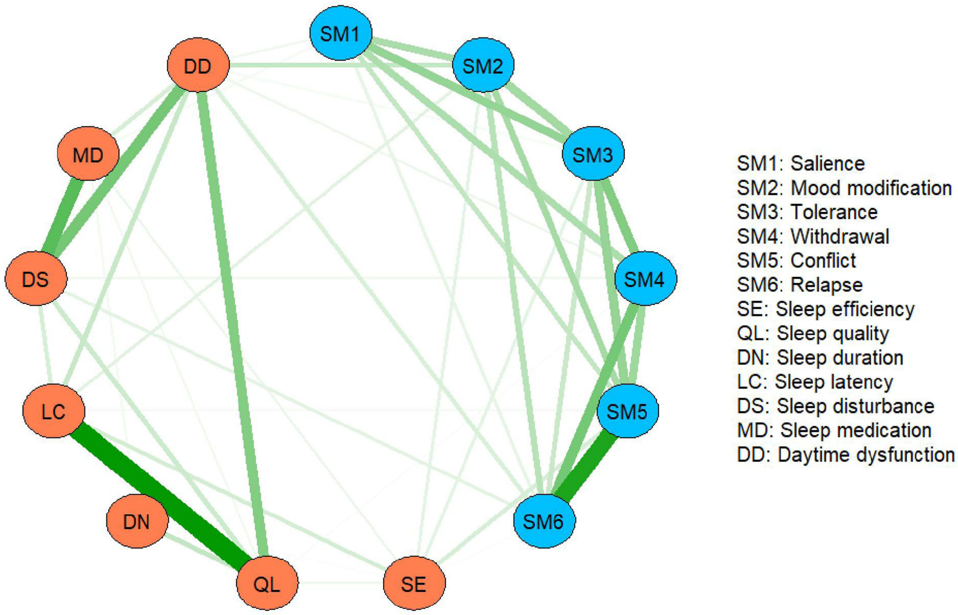

Figure 1 Network structure of social media addiction (SMA) symptoms and sleep-quality components (Gaussian Graphical Model via EBICglasso). Edge thickness indicates regularized partial correlation magnitude; green intensity reflects strength. SMA nodes (SM1–SM6) and PSQI nodes (SE, QL, DN, LC, DS, MD, DD) are colored by domain.
Abbreviations: SM1, Salience; SM2, Mood modification; SM3, Tolerance; SM4, Withdrawal; SM5, Conflict; SM6, Relapse; SE, Sleep efficiency; QL, Subjective sleep quality; DN, Sleep duration; LC, Sleep latency; DS, Sleep disturbance; MD, Use of sleeping medication; DD, Daytime dysfunction.

subnetwork, QL (Sleep Quality) and LC (Sleep Latency), along with DS (Sleep Disturbance) and MD (Sleep Medication Use), exhibited the strongest associations, suggesting significant internal coherence within sleep-related impairments. Additionally, cross-domain associations were identified between SMA and sleep components, with the strongest links observed between SM6 (Relapse) and DD (Daytime Dysfunction), followed by SM2 (Mood Modification) and DD (Daytime Dysfunction). These findings highlight associations between problematic social media use and sleep-related daytime impairments.

Network Centrality

The network centrality measures, such as strength, closeness, and betweenness for all nodes in the network comprising SMA symptoms and sleep quality components are presented in Figure 2.

In terms of strength centrality, which reflects how directly connected a node is to others in the network, SM6 (Relapse) and SM5 (Conflict) emerged as the most central nodes. This indicates that these two SMA symptoms have the strongest overall connections with other symptoms and sleep components. Among the sleep variables, QL (Sleep Quality) and DD (Daytime Dysfunction) showed relatively high strength, suggesting they are central in the sleep-related subnetwork and may serve as key indicators of overall sleep problems.

Closeness centrality, representing how easily a node can be reached from other nodes via the shortest paths, was also highest for SM6, followed by SM5 and SM4 (Withdrawal). This suggests that these nodes are efficiently positioned within the network, potentially influencing or being influenced by other symptoms rapidly.

For betweenness centrality, which indicates a node's role in bridging other nodes, DD (Daytime Dysfunction) showed the highest value, followed by QL (Sleep Quality) and SM2 (Mood Modification). These nodes likely act as key connectors between the SMA and sleep domains, facilitating the flow of influence across otherwise separate symptom clusters.

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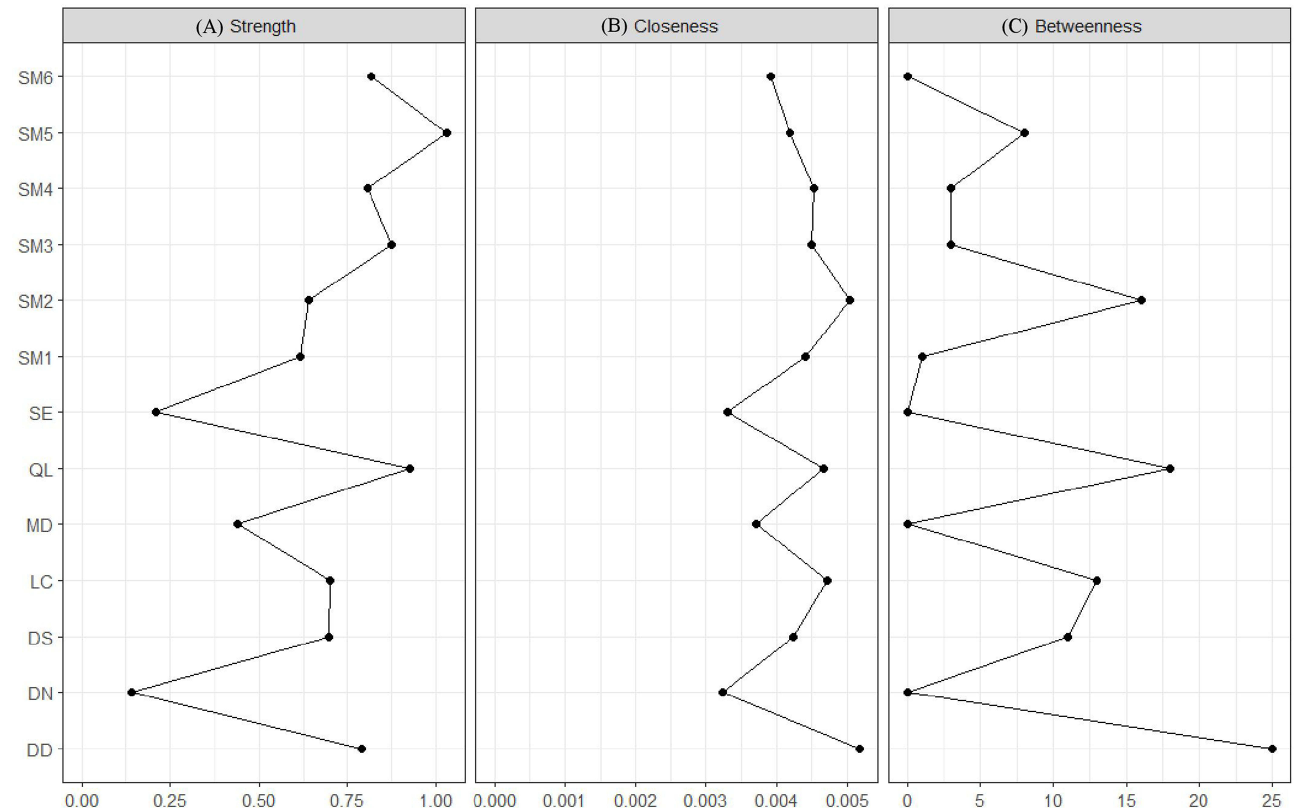

Figure 2 Centrality indices for all nodes in the SMA–sleep network. (**A**) Strength, (**B**) Closeness, (**C**) Betweenness. Higher values indicate greater relative importance within the network topology.
Abbreviations: SM1, Salience; SM2, Mood modification; SM3, Tolerance; SM4, Withdrawal; SM5, Conflict; SM6, Relapse; SE, Sleep efficiency; QL, Subjective sleep quality; DN, Sleep duration; LC, Sleep latency; DS, Sleep disturbance; MD, Use of sleeping medication; DD, Daytime dysfunction.

Bridge Centrality

Bridge centrality analysis was conducted to identify key variables that act as connectors between the social media addiction (SMA) and sleep quality domains (Figure 3). Among all nodes, Daytime Dysfunction (DD) demonstrated the highest bridge strength, indicating its strong involvement in linking the two symptom clusters. Additionally, Mood Modification (SM2) and Sleep Latency (LC) showed notable bridge strength values, suggesting their roles in facilitating interactions between SMA symptoms and sleep-related impairments.

In terms of bridge betweenness, which reflects how often a node lies on the shortest path between nodes in different communities, DD again ranked highest. This finding suggests that DD is a central intermediary in the network. SM2 and LC also showed relatively high betweenness scores, reinforcing their significance as potential points of cross-domain connectivity.

Bridge closeness centrality revealed that DD and SM2 had the shortest average distances to nodes in the opposite community, suggesting their efficient roles in transmitting information between the SMA and sleep networks. In contrast, Sleep Duration (DN) displayed lower closeness, indicating a more peripheral role in cross-domain communication.

The bridge expected influence metrics—both 1-step and 2-step—identified DD, SM2, and LC as the strongest nodes in terms of both direct and indirect influence across communities. These nodes may be particularly important in sustaining or transferring activation between behavioral addiction and sleep disturbance symptoms.

Community detection confirmed the presence of two distinct symptom clusters: one consisting of SMA symptoms (SM1–SM6) and the other of sleep-related components (SE, QL, DN, LC, DS, MD, and DD). Despite this modularity, DD, LC, and SM2 emerged as key bridge nodes linking the two communities.

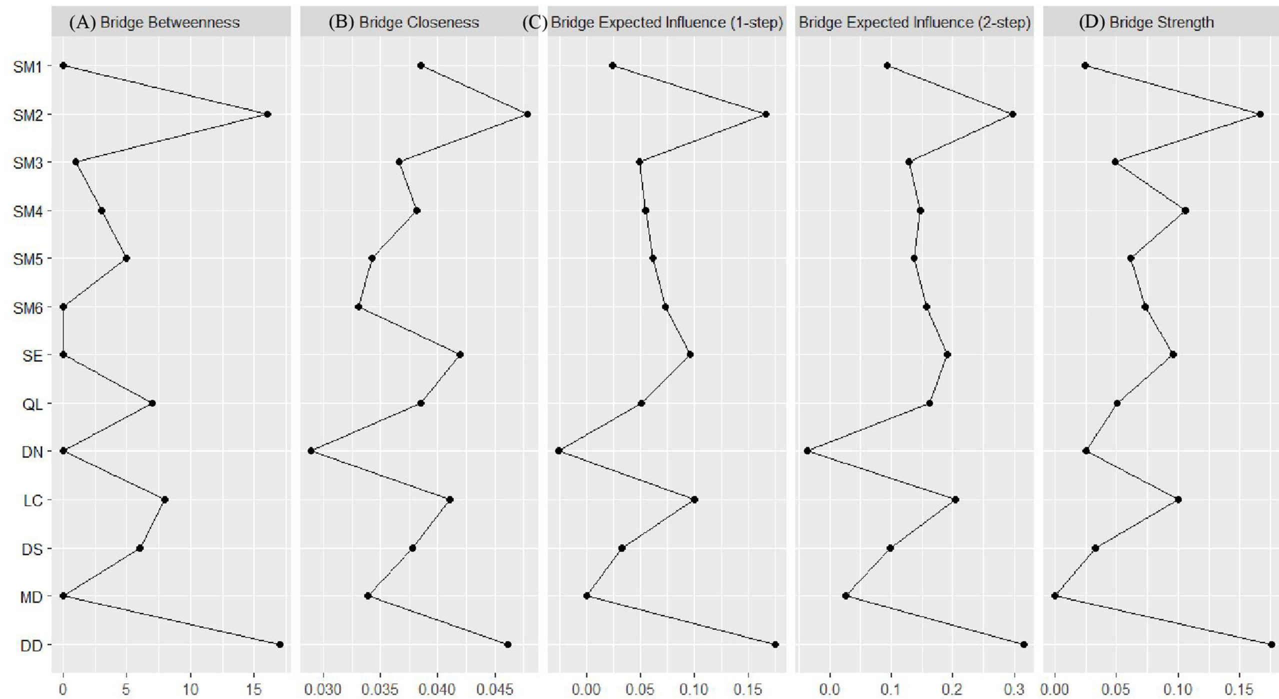

Figure 3 Bridge centrality metrics identifying nodes that connect SMA and sleep communities. (**A**) Bridge betweenness, (**B**) Bridge closeness, (**C**) Bridge expected influence (1-step, 2-step), (**D**) Bridge strength. DD, SM2, and LC demonstrate the highest bridge indices.
Abbreviations: SM1, Salience; SM2, Mood modification; SM3, Tolerance; SM4, Withdrawal; SM5, Conflict; SM6, Relapse; SE, Sleep efficiency; QL, Subjective sleep quality; DN, Sleep duration; LC, Sleep latency; DS, Sleep disturbance; MD, Use of sleeping medication; DD, Daytime dysfunction.

Network Stability and Accuracy

The robustness of the estimated network was evaluated using both case-dropping bootstrap methods to assess centrality stability and nonparametric bootstrap methods to assess edge weight accuracy.

Centrality stability was assessed using a case-dropping subset bootstrap procedure. The CS coefficient for both edge weights and strength centrality was 0.75, the highest level evaluated, indicating excellent stability. This suggests that centrality estimates, particularly node strength remained highly correlated with the original network even when up to 75% of the sample was randomly dropped. As shown in Figure 4, the correlation between original and subset-based strength centrality estimates remained close to 1 across all levels of case-dropping, demonstrating that the network's core structure is reliable and robust across different sample sizes.

Edge weight accuracy was assessed using a nonparametric bootstrap procedure with 1000 iterations. Figure 5 displays the bootstrap-derived 95% confidence intervals for all estimated edges. Red dots represent the original sample estimates, while black dots indicate the bootstrap means. Edges such as SM5–SM6, SM3–SM4, and QL–LC showed narrow confidence intervals, indicating a high degree of precision in their estimation. In contrast, several weaker edges displayed wider intervals, and in some cases, the intervals included zero, suggesting greater uncertainty in those connections. Overall, these findings suggest that the estimated network was both accurate and stable.

Network Comparison of Gender

The network structure of social media addiction and sleep quality among males and females are presented in Figures 6 and 7, respectively. The network structure differed significantly between the two groups (male vs female) ($M= 0.203$, $p =0.013$). This implies that the way social media addiction and sleep quality variables interrelate may be structurally different for males and females. However, the global strength of the networks did not significantly differ between groups, with values 4.449 for males

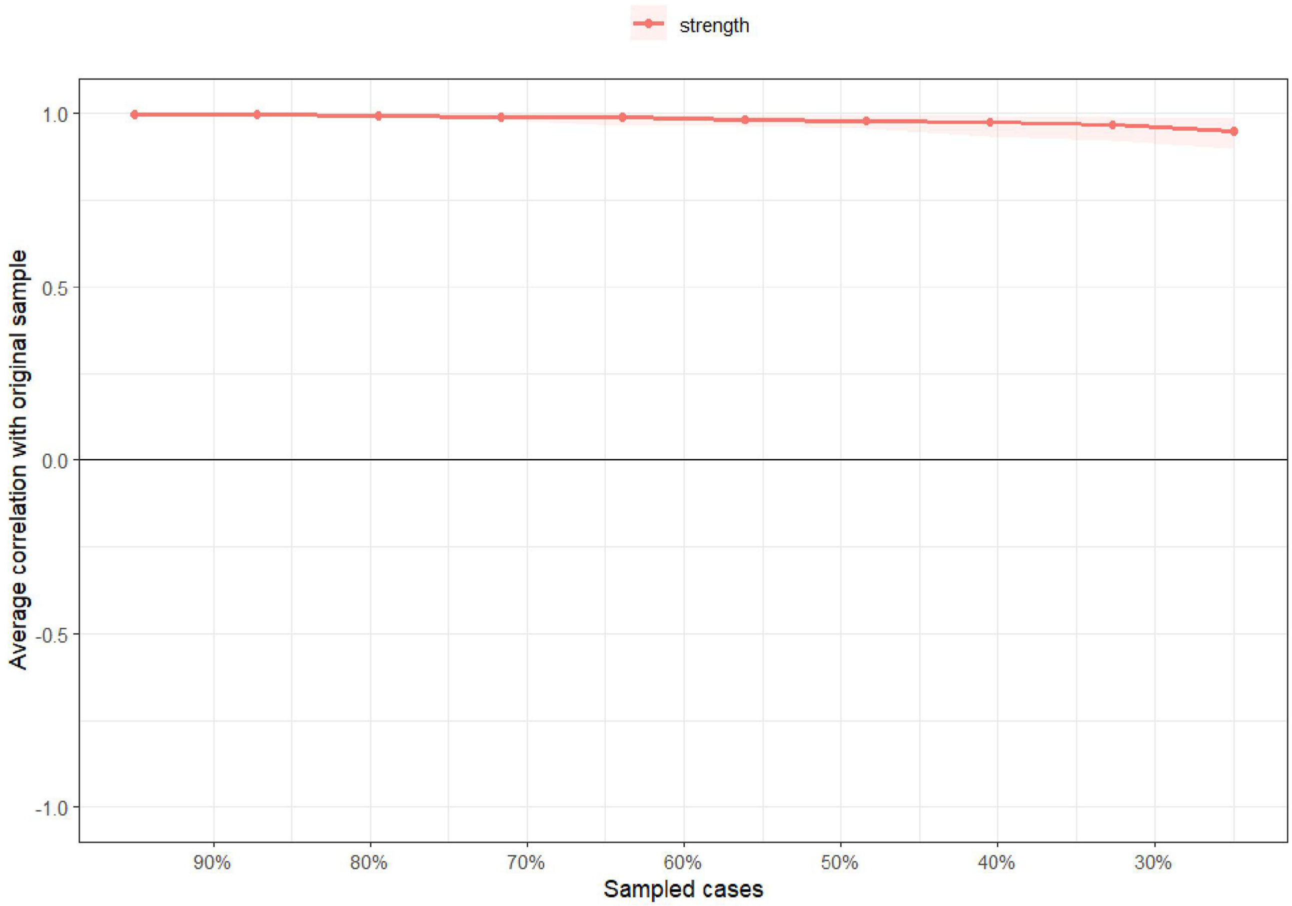

Figure 4 Network stability (case-dropping bootstrap). Correlation stability (CS) coefficients and plots indicate robustness of centrality estimates across subsamples.
Abbreviations: SM1, Salience; SM2, Mood modification; SM3, Tolerance; SM4, Withdrawal; SM5, Conflict; SM6, Relapse; SE, Sleep efficiency; QL, Subjective sleep quality; DN, Sleep duration; LC, Sleep latency; DS, Sleep disturbance; MD, Use of sleeping medication; DD, Daytime dysfunction.

compared to 4.456 for females ($S= 0.007$, $p = 0.991$). This means both groups have networks with comparable overall levels of association strength, even though the specific connections may vary.

Node Centrality Analysis by Gender

Figure 8 presents a comparative analysis of node centrality indices—Strength, Closeness, Betweenness, and Expected Influence—between male and female participants. Overall, the centrality patterns were largely similar across genders, indicating a broadly consistent network structure. However, some variations in the magnitude of centrality metrics were observed, particularly for specific nodes.

In terms of strength centrality, which reflects the overall connectivity of a node, both males and females showed highest values for SM5 (Conflict) and QL (Sleep Quality), suggesting these nodes are densely connected in both groups. Notably, SM6 (Relapse) displayed higher strength in females compared to males, whereas QL showed slightly greater strength in males.

For closeness centrality, which captures how easily a node can reach all other nodes in the network, DD (Daytime Dysfunction) demonstrated the highest closeness for both genders, with females showing a marginally higher score. This suggests that daytime dysfunction may act as a central conduit for the propagation of effects across both domains, particularly among females.

With respect to betweenness centrality, which indicates how often a node lies on the shortest path between other nodes, DD again emerged as the most prominent node among females, indicating its potential role as a key intermediary

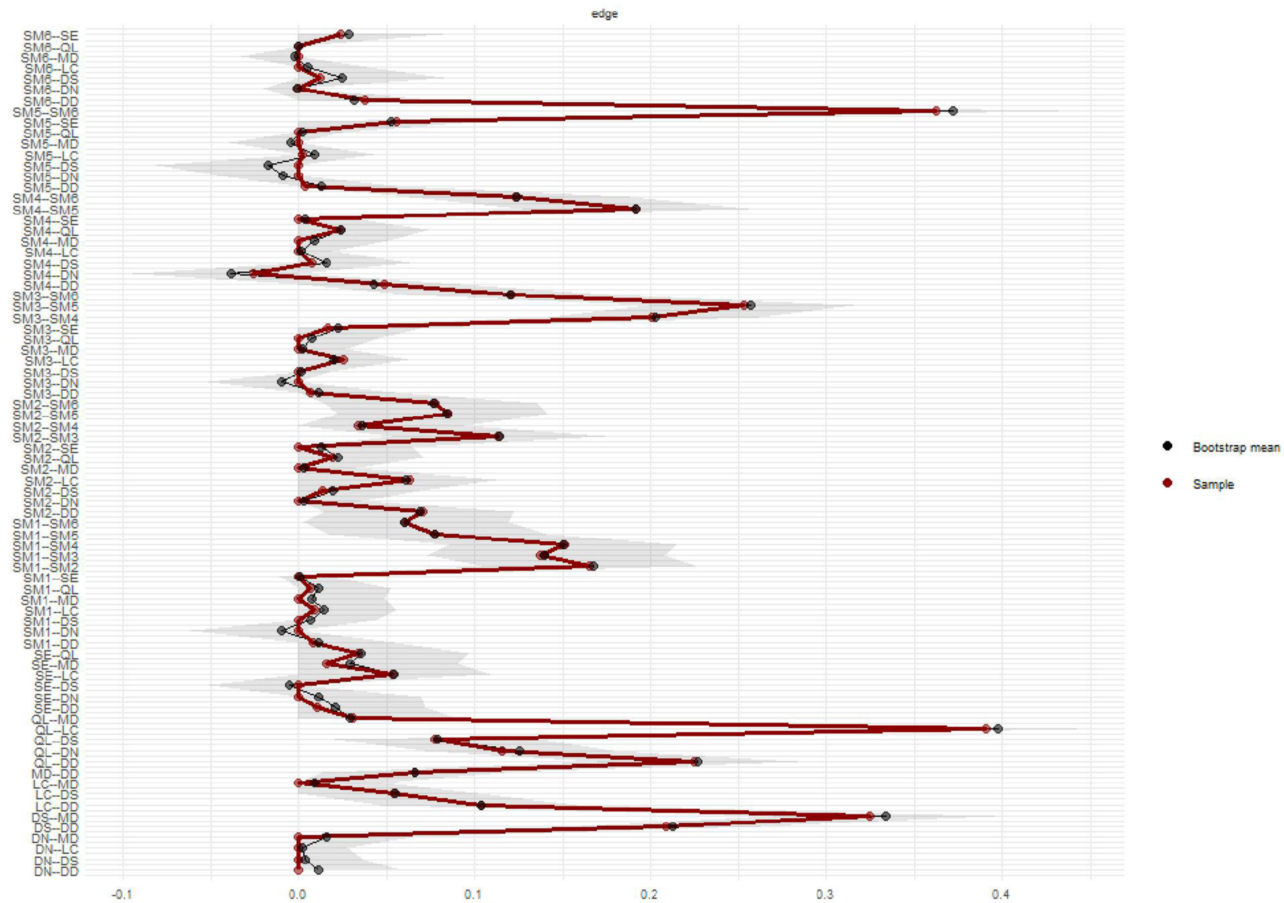

Figure 5 Edge-weight accuracy (nonparametric bootstrap, 1000 iterations). Points show original estimates; bars show 95% bootstrap confidence intervals. Narrow intervals denote higher precision.

Abbreviations: SM1, Salience; SM2, Mood modification; SM3, Tolerance; SM4, Withdrawal; SM5, Conflict; SM6, Relapse; SE, Sleep efficiency; QL, Subjective sleep quality; DN, Sleep duration; LC, Sleep latency; DS, Sleep disturbance; MD, Use of sleeping medication; DD, Daytime dysfunction.

in the network. In contrast, QL (Sleep Quality) had the highest betweenness among males, suggesting that perceived sleep quality may be more influential in bridging symptom clusters in males.

Expected influence, which incorporates both positive and negative connections, showed a pattern similar to strength. Here, SM5, QL, and SM3 (Tolerance) emerged as the most influential nodes across both groups, although males exhibited higher expected influence values for QL and SM3, while females showed slightly elevated values for SM6 and DD.

These gender-based differences in centrality metrics suggest that while the structural configuration of the network is stable across sexes, the relative importance of individual symptoms may differ. Specifically, DD, SM5, and QL appear to serve as critical hubs for both groups, but their influence varies slightly depending on gender—highlighting the value of stratified network analysis in uncovering nuanced symptom dynamics.

Edge Invariance Across Gender

The Edge Invariance Test revealed statistically significant gender-based differences in several key associations between nodes within the network of SMA symptoms and sleep-related problems (Table 3). Notably, a significant difference was observed between SM4 (Withdrawal) and SM6 (Relapse) (p = 0.001), suggesting that the relationship between withdrawal symptoms and relapse behaviors is notably stronger or weaker depending on gender. This indicates that individuals may differ in how disengagement from social media contributes to relapse patterns across male and female groups.

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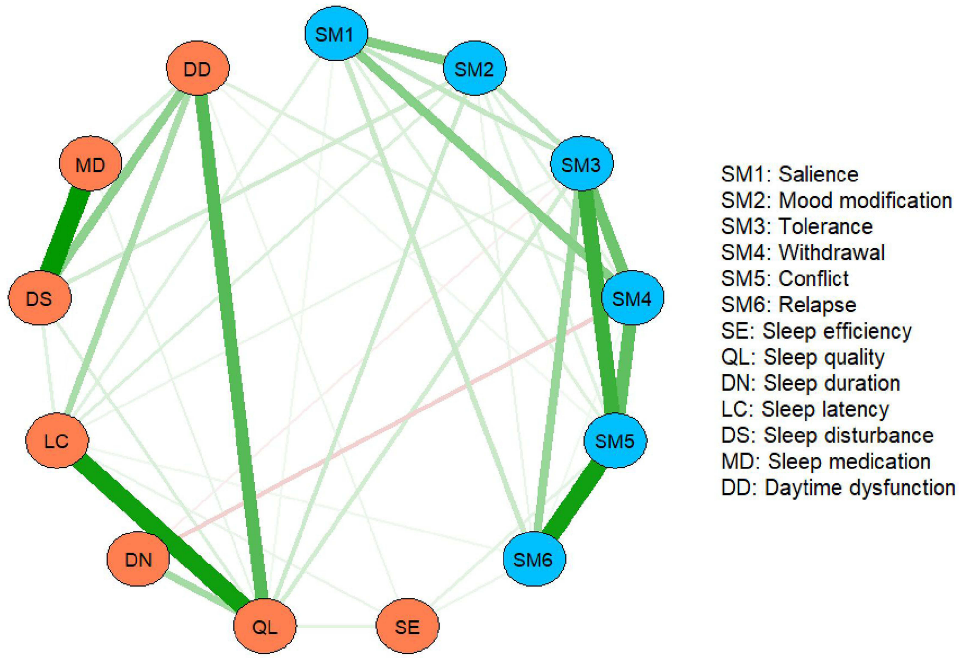

Figure 6 Network structure for males (SMA symptoms and PSQI components). Visualization parameters and scaling match Figure 1 for comparability.
Abbreviations: SM1, Salience; SM2, Mood modification; SM3, Tolerance; SM4, Withdrawal; SM5, Conflict; SM6, Relapse; SE, Sleep efficiency; QL, Subjective sleep quality; DN, Sleep duration; LC, Sleep latency; DS, Sleep disturbance; MD, Use of sleeping medication; DD, Daytime dysfunction.

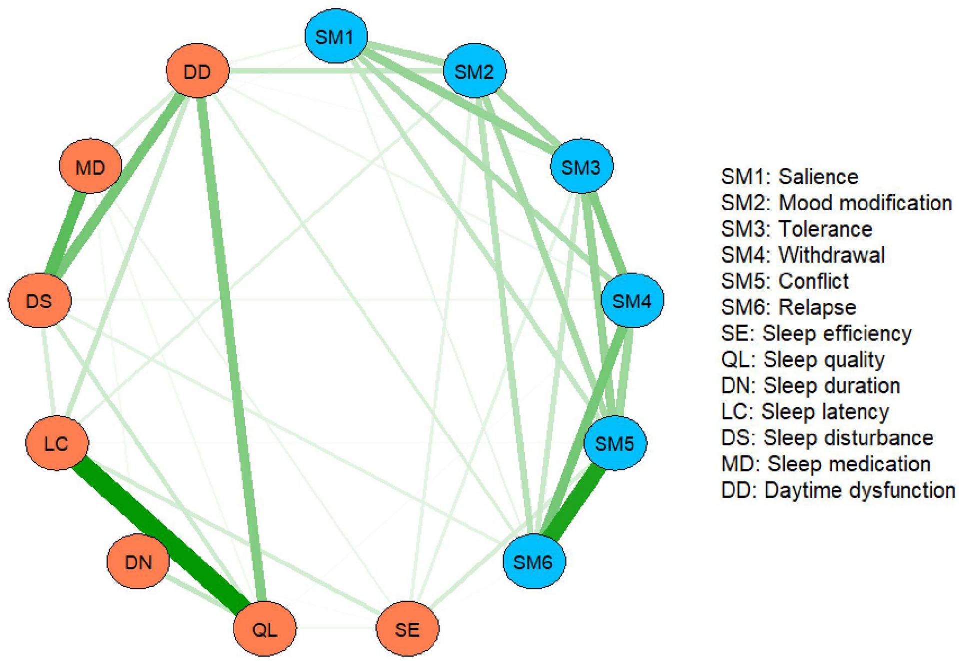

Figure 7 Network structure for females (SMA symptoms and PSQI components). Visualization parameters and scaling match Figure 1 for comparability.
Abbreviations: SM1, Salience; SM2, Mood modification; SM3, Tolerance; SM4, Withdrawal; SM5, Conflict; SM6, Relapse; SE, Sleep efficiency; QL, Subjective sleep quality; DN, Sleep duration; LC, Sleep latency; DS, Sleep disturbance; MD, Use of sleeping medication; DD, Daytime dysfunction.

A second significant edge difference emerged between SM3 (Tolerance) and QL (Sleep Quality) (p = 0.002), implying that the extent to which increasing tolerance toward social media impacts perceived sleep quality varies between groups. Similarly, SM2 (Mood Modification) showed differential associations with both DS (Sleep

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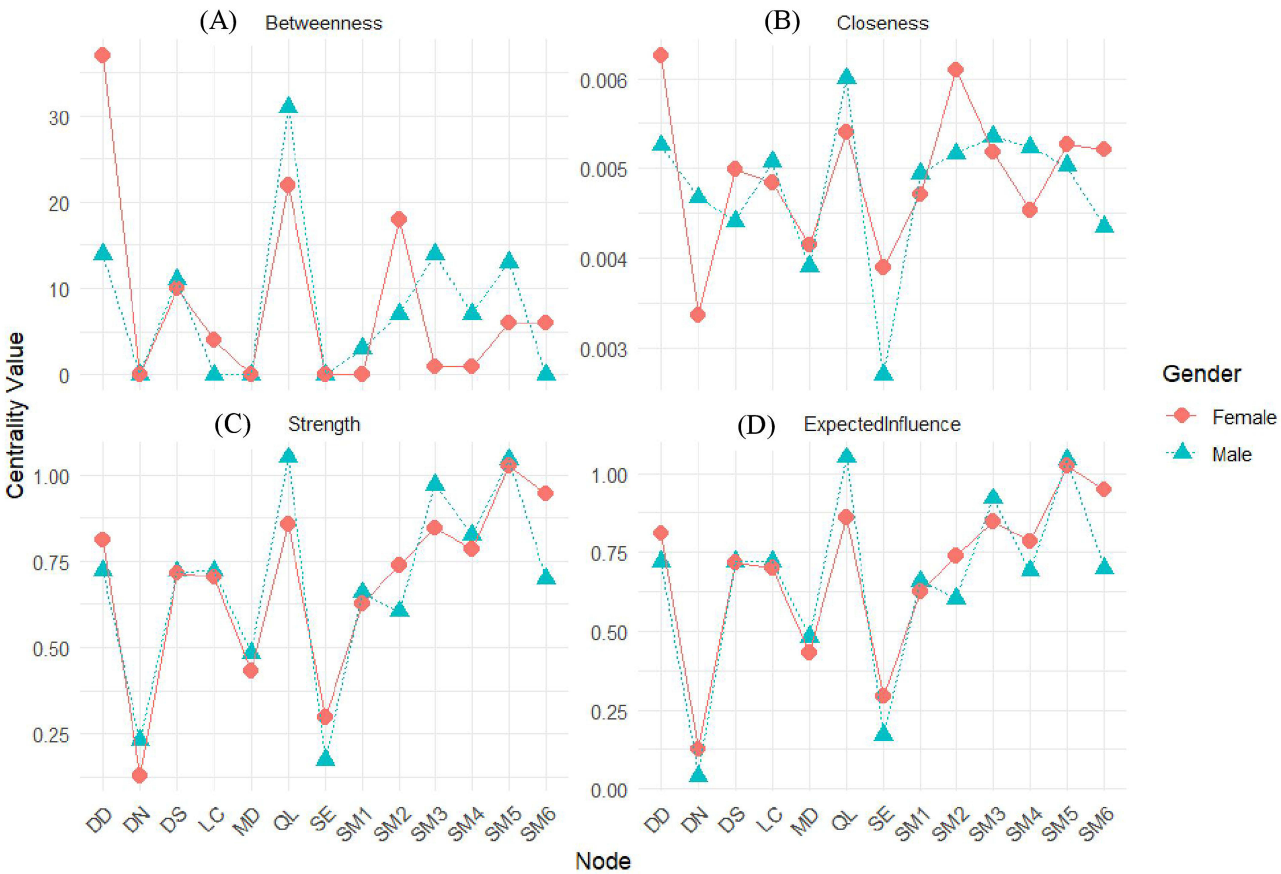

Figure 8 Centrality comparison by gender. (**A**) Betweenness, (**B**) Closeness, (**C**) Strength, (**D**) Expected influence. Lines/markers denote gender (female = circles; male = triangles).
Abbreviations: SM1, Salience; SM2, Mood modification; SM3, Tolerance; SM4, Withdrawal; SM5, Conflict; SM6, Relapse; SE, Sleep efficiency; QL, Subjective sleep quality; DN, Sleep duration; LC, Sleep latency; DS, Sleep disturbance; MD, Use of sleeping medication; DD, Daytime dysfunction.

Disturbance) ($p = 0.025$) and QL (Sleep Quality) ($p = 0.028$), indicating that the role of emotional regulation via social media in sleep disruption and quality is not uniform across genders. Although the NCT evaluated all possible edges between nodes, only those showing meaningful or near-significant variation ($p < 0.10$) were presented in Table 3 to ensure interpretability and transparency in gender-based comparisons. This approach aligns with best practices in network psychometrics, which recommend summarizing theoretically meaningful differences rather than exhaustively listing all pairwise comparisons.[30]

Table 3 Edge Invariance Across Genders

Node 1	Node 2	p-value	Test Statistic (E)	Interpretation
SM4	SM6	0.001	0.202	Significant variation, indicating altered connectivity between withdrawal and relapse symptoms.
SM3	QL	0.002	0.067	Strong indication that tolerance affects sleep quality differently across conditions.
SM2	QL	0.028	0.076	Possible structural variation in how mood modification links to sleep quality.
SM2	DS	0.025	0.069	Mood modification impacts sleep disturbance differently across groups.
SM2	DD	0.074	0.095	No evidence of variability in mood dependency and daytime dysfunction.
SM1	LC	0.078	0.046	No difference in interaction between salience symptoms and sleep latency.

(*Continued*)

Table 3 (Continued).

Node 1	Node 2	p-value	Test Statistic (E)	Interpretation
QL	DN	0.546	0.036	No strong difference detected in sleep quality and daytime dysfunction relationship.
DS	MD	0.089	0.109	No evidence that sleep disturbance influences medication use differently across groups.
LC	DD	0.485	0.035	No substantial evidence of variation in sleep latency's role in daytime dysfunction.

Abbreviation: E, edge invariance statistics from NCT; SM1, Salience; SM2, Mood modification; SM3, Tolerance; SM4, Withdrawal; SM5, Conflict; SM6, Relapse; SE, Sleep efficiency; QL, Subjective sleep quality; DN, Sleep duration; LC, Sleep latency; DS, Sleep disturbance; MD, Use of sleeping medication; DD; Daytime dysfunction.

Discussion

This study applied a network analytic approach to examine the interplay between SMA symptoms and sleep quality components among Bangladeshi adolescents. The analysis revealed that SMA and sleep quality formed two distinct yet interconnected symptom clusters. Within the SMA subnetwork, strong connections emerged between conflict and relapse, and between tolerance and withdrawal. In the sleep domain, tight associations were found between sleep quality and sleep latency, as well as between sleep disturbance and medication use. Bridge centrality analysis identified daytime dysfunction (DD), mood modification (SM2), and sleep latency (LC) as key nodes connecting the two domains. Moreover, network comparison revealed significant structural differences in symptom associations between males and females, though overall network strength was statistically equivalent across groups.

One of the central findings was the identification of SM5 (Conflict) and SM6 (Relapse) as the most interconnected SMA symptoms, reflecting previous research indicating that problematic social media use often results in interpersonal difficulties and challenges in self-regulation.[1,6,24] These results also align with the components model of addiction,[31] where conflict and relapse exemplify the core mechanisms of salience, loss of control, and reinstatement following failed abstinence. Similarly, the strong association between SM3 (Tolerance) and SM4 (Withdrawal) further supports the behavioral addiction framework[31] and the Interaction of Person-Affect-Cognition-Execution (I-PACE) model,[32] which conceptualizes addictive behaviors as the outcome of interactions between affective dysregulation, cognitive biases, and impaired executive control. In this context, the co-activation of tolerance, withdrawal, and relapse illustrates how emotion-driven digital engagement sustains maladaptive cycles of use that parallel substance-related addictions.

Within the sleep domain, the association between sleep quality (QL) and sleep latency (LC) reflects established findings that delayed sleep onset is a primary factor of subjective poor sleep.[5] Furthermore, the strong association between DS (Sleep Disturbance) and MD (Medication Use) suggests that individuals experiencing frequent nocturnal disruptions may rely more heavily on pharmacological aids to manage their sleep. These patterns support theoretical models of behavioral dysregulation such as I-PACE model,[32] in which impaired emotion regulation and reward sensitivity extend beyond online activity to disturb restorative physiological processes such as sleep.

Importantly, cross-domain associations showed links between SMA symptoms and sleep outcomes. The strong connection between relapse (SM6) and daytime dysfunction (DD) suggests that inability to regulate social media use may be linked to impairments in daytime functioning, such as reduced alertness, increased fatigue, or lower academic productivity. This is consistent with prior studies demonstrating that social media overuse is associated with delayed sleep-onset, reduced sleep duration, and poorer daytime performance.[2,8] Additionally, mood modification (SM2) was associated with both DD and sleep efficiency (SE). The prominence of mood modification and relapse further reinforces the I-PACE[32] and Compensatory Internet Use Models,[33] which posit that individuals engage with online platforms to regulate mood or escape negative affect, patterns that are associated with reduced sleep efficiency and poorer daytime performance. These findings highlight how maladaptive coping and self-regulation failures function as shared mechanisms linking SMA and poor sleep, underscoring the need for interventions targeting emotional regulation skills.

The findings should also be interpreted within the sociocultural context of Bangladesh, where smartphone ownership and social media engagement have increased dramatically among adolescents and young adults in recent years. Previous studies have shown that excessive social media use is associated with sleep disturbance among Bangladeshi

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adolescents,[34] and that social media addiction is significantly linked to poorer sleep quality among university students.[16] Additionally, the highly competitive academic environment in Bangladesh may also be linked to digital dependency, as students increasingly rely on social media for stress relief and peer interaction during exam preparation periods.[22] These patterns reflect the widespread prevalence of late-night screen exposure and inadequate sleep hygiene among adolescents and youth in Bangladesh. Addressing these challenges through culturally informed digital-wellbeing and sleep-health interventions in schools and universities may therefore be particularly valuable.

The bridge centrality analysis identified daytime dysfunction (DD) as a major bridge node, highlighting its dual role in both SMA and sleep-related symptom propagation. As one of the most consistently reported consequences of poor sleep, DD may also serve as an indirect indicator of behavioral dysregulation caused by problematic social media use.[19] Although DD is conceptually part of sleep quality, its bridging role in the network does not indicate circular reasoning. Instead, DD captures the behavioral and cognitive consequences of poor sleep that overlap with excessive social media use, such as fatigue, inattention, and reduced productivity, thus serving as a functional connector between sleep-related and behavioral dysregulation pathways. Its central bridging role suggests that impaired daytime functioning may be associated with disrupted sleep and compulsive digital behaviors. In addition, sleep latency (LC) and mood modification (SM2) emerged as significant bridge symptoms, indicating that both physiological factors (eg, delayed sleep onset) and emotional-cognitive processes (eg, using social media to regulate mood) are central pathways through linking SMA with sleep impairment. These findings suggest that targeted interventions focusing on these bridge nodes, particularly DD, LC, and SM2 may simultaneously reduce symptoms across both domains, offering a more integrated and efficient approach to prevention and treatment.

Gender-based comparisons revealed meaningful differences in both social media addiction and sleep quality. Females showed poorer sleep quality, consistent with prior studies linking women's greater sleep vulnerability to emotional and cognitive factors such as rumination and stress sensitivity.[35–37] Males, however, reported higher SMA scores, possibly reflecting gendered use motives. Men often engage for entertainment or information, whereas women use social media for emotional connection and validation. These distinctions may reflect underlying gender norms in Bangladesh, where women face greater social expectations regarding connectedness and emotional expression, while men have more autonomy in leisure and technology use. Kircaburun et al similarly found that social and entertainment motives, along with traits such as neuroticism and introversion, predicted problematic social media use, supporting the idea that personality and motives influence both engagement intensity and its psychological effects.[38] However, other studies have reported higher SMA among females,[39] suggesting a complex interplay of emotion regulation, sociocultural factors, and digital access patterns. Taşkaya et al also identified a positive association between smartphone addiction and poor sleep quality, underscoring the role of emotional dependency and late-night technology use in gender-linked sleep disturbances.[40]

The gender-based network comparison revealed meaningful structural differences in how social media addiction (SMA) and sleep quality components interact. Specifically, sleep quality (QL) emerged as more central in the male network, suggesting that perceptions of sleep quality play a more prominent role in how sleep problems manifest among males. In contrast, relapse (SM6) was more central among females, indicating greater difficulty in disengaging from social media and potentially stronger emotional and behavioral consequences related to compulsive use. These findings align with previous literature showing that females often display greater emotional investment in social media use and are more susceptible to sleep disturbances resulting from nighttime digital engagement.[4,18] Further supporting these distinctions, the edge invariance test revealed significant gender-based variations in the strength of key symptom-to-symptom connections, such as withdrawal–relapse and tolerance–sleep quality. These differences suggest that symptom dynamics may be partially moderated by gender, highlighting the value of stratified analyses in understanding individual differences in digital behavior and sleep health.

From a methodological perspective, the high correlation stability coefficient (CS = 0.75) and narrow bootstrapped confidence intervals for key edges support the robustness of the estimated network. These results lend confidence to the observed associations and reinforce the value of network analysis in mapping the dynamic interactions between digital behaviors and health outcomes.

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Practical Implications

Findings suggest practical implications for educational and clinical settings. School- and university-based mental health programs could incorporate psychoeducational workshops on digital well-being, time management, and sleep hygiene to address key bridge symptoms such as daytime dysfunction and mood modification. Given the observed gender differences, interventions should also be gender-sensitive, addressing emotional regulation and connectedness among females and promoting balanced technology use and stress management among males. Targeting these bridge symptoms may be beneficial for addressing both excessive social media use and sleep disturbances simultaneously. Moreover, integrating digital literacy and behavioral self-regulation modules into student counseling and wellness services could foster healthier technology use. Evidence-based interventions such as cognitive-behavioral therapy for insomnia (CBT-I)[41] and mindfulness-based programs[42] have demonstrated promising results in improving sleep quality. Structured screen-time reduction plans and digital hygiene initiatives may help restore healthier circadian rhythms and promote restorative sleep.[43] Adapting these strategies to the Bangladeshi educational and cultural context could provide sustainable approaches for enhancing sleep and digital health among adolescents and young adults.

Strength and Limitations

This study offers several notable strengths. First, it is among the few to apply a network analytic framework to examine the interrelations between social media addiction (SMA) and sleep quality, allowing for a nuanced, symptom-level understanding of their interactions. By identifying central and bridge symptoms, the analysis moves beyond traditional variable-centered approaches and highlights potential intervention targets. Additionally, the inclusion of gender-based network comparisons adds valuable insights into how symptom structures may differ across demographic subgroups, offering implications for more tailored interventions.

However, several limitations should be acknowledged. The cross-sectional design limits the ability to draw conclusions about causality or the temporal sequence of symptom interactions. While network analysis is valuable for mapping complex associations between SMA and sleep quality, it does not capture directionality or temporal dynamics. Future research employing longitudinal or temporal network designs is needed to clarify causal pathways and dynamic changes over time. The use of convenience sampling may introduce selection bias; however, this approach was chosen due to the unique setting of entrance examinations, where students from across Bangladesh gather in one location. All data were self-reported, which may be subject to recall and social desirability biases. Additionally, the sample comprised recent high school graduates preparing for university entrance and may not represent adolescents from different socioeconomic backgrounds, rural areas, or those not pursuing higher education. Future studies should aim to replicate these findings across more diverse and representative populations. Moreover, although the EBICglasso approach uses regularization to reduce overfitting, network models with several nodes may still produce weak or spurious edges. Therefore, such connections should be interpreted cautiously, and future studies are encouraged to validate these findings using larger or longitudinal datasets. Lastly, although network analysis provides a detailed map of symptom associations, the method is still developing, and findings should be interpreted with caution and replicated across settings to ensure reliability and external validity.

Conclusion

This study applied a network analytic approach to investigate the complex relationships between social media addiction symptoms and sleep quality components among 1139 Bangladeshi high school graduates. The findings reveal distinct but interconnected symptom clusters, with key nodes, such as relapse, conflict, sleep quality, and daytime dysfunction emerging as central within the network. Bridge centrality analyses identified daytime dysfunction, mood modification, and sleep latency as critical pathways linking SMA and sleep disturbances, emphasizing their potential as intervention targets.

The results further highlight gender-based differences in both SMA and PSQI scores; and gender-specific patterns in network structure, suggesting that males and females may experience and express SMA and sleep problems differently.

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Such differences emphasize the importance of considering demographic factors when designing prevention and treatment strategies.

From a practical perspective, interventions that specifically target daytime dysfunction and mood modification, such as school- or university-based programs promoting healthy digital habits, stress management, and sleep hygiene, may effectively enhance sleep quality among adolescent social media users. Overall, this study advances the understanding of how digital behaviors intersect with sleep health by uncovering symptom-level interactions that can inform focused and evidence-based behavioral interventions.

Data Sharing Statement

The dataset associated with this paper is available from the corresponding author upon reasonable request.

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Author Contributions

FAM: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Software; Validation; Visualization; Writing - original draft; and Writing - review & editing. **MAM**: Data curation; Investigation; Methodology; Project administration; Resources; Validation; Visualization; and Writing - review & editing. **MMA**: Funding acquisition; Investigation; Resources; Validation; Visualization; and Writing - review & editing. **DG**: Investigation; Methodology; Resources; Supervision; Validation; Visualization; Writing - original draft; and Writing - review & editing. All authors gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors have no conflicts of interest to disclose.

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