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The Relationship Between Digital Addiction and Health Risk Behaviors Among University Students: A Computer-Simulated Network Analysis

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Abstract

Background

Digital addiction is closely associated with health risk behaviors among university students. This study aimed to explore the internal symptom association patterns between digital addiction and health risk behaviors using network analysis and to conduct computer-simulated interventions using the NodeIdentifyR algorithm (NIRA) within the Ising model to identify potential targets for prevention and alleviation.

Methods

A total of 1,916 university students from Gansu Province were recruited. Digital addiction was assessed using the Smartphone Addiction Scale-Short Version (SAS-SV), Bergen Social Media Addiction Scale (BSMAS), and Internet Gaming Disorder Scale-Short Form (IGDS9-SF), while health risk behaviors were assessed using the Adolescent Health Related Risky Behavior Inventory (AHRBI). A network of digital addiction and health risk behaviors was constructed to examine the complex relationships among the variables.

Results

Network analysis showed that aggression and violent behaviors had the highest expected influence, followed by rule-breaking behaviors. Gaming disorder had the highest bridge expected influence, followed by aggression and violent behaviors. The directed acyclic graph (DAG) suggested that social media addiction may be located at a relatively high level of the network structure and was associated with multiple variables through directed relationships. Computer-simulated interventions showed that reducing rule-breaking behaviors and increasing aggression and violent behaviors produced relatively large effects on the overall network, suggesting that these two nodes may be potential candidates for further investigation in future intervention research.

Conclusions

This study used network analysis and computer-simulated interventions to explore the relationship between digital addiction and health risk behaviors among university students. The findings suggest that future intervention research may benefit from focusing on aggression and violent behaviors and rule-breaking behaviors, while also emphasizing the early identification of social media addiction to promote the health and well-being of university students.

1 Introduction

Health risk behavior refers to behavioral patterns that violate social health standards and cause harm to health (Kannas, 1982). It includes aggressive and violent behaviors, rule-breaking behaviors, unprotected sexual behaviors, suicidal and self-harm behaviors, smoking and drinking behaviors, and health-

threatening behaviors (Wang et al., 2012). Health risk behaviors are closely associated with the occurrence of diseases (Zhang et al., 2005), such as increasing the risk of chronic cardiovascular diseases, obesity, diabetes, anxiety, and depression (Liu et al., 2022). Studies have shown that college students commonly exhibit one or more health risk behaviors (Wang et al., 2023; Xiang et al., 2025), such as smoking, drinking, and unhealthy dietary behaviors (Bellis et al., 2022; Zhang et al., 2020). The college period is a critical stage for physical and psychological development. The behavioral habits and lifestyles formed during this period may have profound effects on their future health development (Dietz et al., 2020). Therefore, identifying the influencing factors of health risk behaviors among college students and exploring effective intervention targets have become important research directions for promoting the health development of college students.

1.1 Health risk behaviors

In recent years, health risk behaviors among college students have become an important issue of concern in the field of public health, and multiple health risk behaviors are prevalent among college students (Wang et al., 2023; Xiang et al., 2025). Yang et al. (2024) investigated college students and found that the detection rates of insufficient physical activity, smoking, internet addiction, and psychological disorders among college students were 35.9%, 15.4%, 13.2%, and 6.3%, respectively. More than one-third of students had at least one health problem. Liu et al. (2022) investigated 2,150 college students and found that the detection rate of aggressive and violent behaviors was 39.16%, and the detection rate of rule-breaking behaviorss was 28.60%.

It is worth noting that health risk behaviors do not occur independently. Problem Behavior Theory suggests that different health risk behaviors jointly constitute an interconnected behavioral system, and different risk behaviors share common psychosocial foundations and mutually promote each other (Jessor, 1991; Donovan & Jessor, 1985). Previous studies have found that students who simultaneously engage in multiple risk behaviors, such as alcohol abuse, smoking, or cannabis use, have higher rates of mental health problems than those who exhibit only a single category of health risk behavior (Jao et al., 2019). These findings indicate that health risk behaviors usually occur in the form of multiple co-occurring behaviors, and there may be common risk mechanisms underlying these behaviors. Therefore, identifying the key risk factors influencing health risk behaviors among college students is of great significance for revealing their underlying mechanisms and developing precise intervention strategies.

1.2 Digital addiction and health risk behaviors

In recent years, digital addiction has become an important behavioral problem affecting the physical and mental health of college students (Kuss & Griffiths, 2017; Meng et al., 2022). Digital addiction refers to the persistent, excessive, and uncontrollable use of digital devices and related activities by individuals, resulting in psychological, social, and functional impairments (Christakis, 2019). It includes various forms of behavioral addiction, such as problematic smartphone use (Problematic Smartphone Use, PSU), social media addiction (Social Media Addiction, SMA), and gaming disorder (Gaming Disorder, GD) (Meng et al., 2022).Previous studies have found that these three types of digital addiction have high

comorbidity (Chang et al., 2023). Therefore, in this study, we conceptualized digital addiction as a multidimensional construct consisting of PSU, SMA, and GD (Chen et al., 2021; Gu et al., 2026). The Health Belief Model (Singh et al., 2020) suggests that distorted perceptions of health threats among addicted individuals may reduce their motivation to participate in health-promoting behaviors.

A large number of studies have shown that digital addiction is closely associated with health risk behaviors. Digital addiction is not only closely related to adverse physical and mental health outcomes such as anxiety, depression, and sleep disorders (Shiferaw et al., 2025; Li et al., 2020), but clinical studies have also shown that it is associated with functional impairments and psychological disorders, including attention-deficit/hyperactivity disorder (Wang et al., 2017), depression (Li et al., 2020), and anxiety (Lopes et al., 2022). In addition, digital addiction is also consistently associated with externalizing behaviors, including aggressive behaviors, impulsive behaviors, and rule violations (Anderson & Bushman, 2002; Kuss & Griffiths, 2017).In summary, digital addiction not only affects the mental health of college students but may also promote the occurrence of multiple health risk behaviors and is an important risk factor for health risk behaviors among college students.

However, previous studies have often examined the relationships between specific digital addictions and health risk behaviors separately (Zhao, 2026; Siddique et al., 2026; Lee & Song, 2024), failing to consider digital addiction and health risk behaviors as an interconnected and coexisting system. The occurrence of one behavior often activates other behaviors. For example, gaming addiction may directly lead to sedentary behavior, which may further result in disrupted sleep rhythms and social avoidance (Dresp-Langley & Hutt, 2022; Masaeli & Billieux, 2022). Kardefelt-Winther (2014) further pointed out that the key to understanding digital addiction lies in focusing on individuals' usage motivations and real-life contexts rather than simply pathologizing addictive behaviors. This suggests that the relationship between digital addiction and health risk behaviors may involve systematic interactions.

1.3 Network Analysis and Computational Simulation

In recent years, network analysis has been increasingly applied in psychological and behavioral science research. Unlike traditional latent variable models, network analysis conceptualizes psychological variables as an interacting system of interconnected components. By identifying central nodes and associations among nodes, this approach provides insights into the underlying structure and potential mechanisms of complex psychological phenomena (Epskamp et al., 2018; Borsboom et al., 2021). Network analysis has been widely applied to the study of depression, anxiety, addiction, and other psychological and behavioral problems (Robinaugh et al., 2020). However, network analysis primarily characterizes associations among variables and has limited capacity to infer potential causal structures. Directed acyclic graphs (DAGs), as graphical models grounded in causal inference, have been widely applied in epidemiology (Greenland et al., 1999), public health (Tennant et al., 2021), and psychological research (Rohrer, 2018). By graphically representing potential causal relationships among variables, DAGs can help identify potential confounding factors and inform variable selection and adjustment strategies (Greenland et al., 1999; Rohrer, 2018).

Furthermore, computational intervention simulations based on network analysis can simulate how changes in the state of individual nodes may affect the network as a whole, thereby identifying potentially valuable intervention targets and providing a scientific basis for developing more precise intervention strategies (Lunansky et al., 2022). This approach has increasingly been applied in clinical psychology (Li et al., 2024; Mei et al., 2026; Yu et al., 2025). However, existing research on digital addiction and health-risk behaviors has primarily focused on identifying network structures and connectivity patterns (Zhao et al., 2026), with limited research integrating computational simulation approaches to further evaluate the potential value of dynamically intervening on different behavioral nodes.

1.4 The Present Study

Against this background, the present study aimed to use network analysis combined with computational intervention simulations to investigate symptom-level associations and potential intervention targets linking digital addiction—including problematic smartphone use (PSU), social media addiction (SMA), and gaming disorder (GD)—with health-risk behaviors among Chinese university students. This approach may provide a theoretical basis for understanding the interrelationships between digital addiction and health-risk behaviors and preliminary empirical evidence for the development of more precise behavioral intervention strategies in the future.

Specifically, the present study sought to: (1) construct a symptom network of digital addiction and health-risk behaviors, identify central and bridge nodes within the network, and determine key symptoms underlying the associations between these two domains; (2) use a directed acyclic graph (DAG) to preliminarily explore potential directional or priority relationships between digital addiction and health-risk behaviors; and (3) conduct computational simulations of both alleviating and aggravating interventions based on the network analysis results to evaluate the effects of interventions targeting different nodes on the overall network and to identify potential candidate nodes that warrant further investigation in future prevention and intervention research.

2 Methods

2.1 Participants

A convenience sampling method was used to recruit 1,926 university students from Gansu Province, China, aged 18–24 years (M = 19.85, SD = 1.19). The questionnaires were administered collectively in classrooms using a paper-and-pencil format. A total of 1,926 questionnaires were distributed, of which 1,758 were considered valid, yielding a valid response rate of 91.28%. Of the participants, 59.3% were female and 40.7% were male.

Body mass index (BMI) is widely used internationally as an indicator of body weight status and general health. According to the criteria specified in the *Guideline for Prevention and Control of Overweight and Obesity in Chinese Adults* (Chen & Kong, 2006), 21.0% of participants in the present sample were

underweight (BMI < 18.5 kg/m²), 60.1% had a normal weight (18.5 ≤ BMI < 23.9 kg/m²), 13.9% were overweight (24.0 ≤ BMI < 27.0 kg/m²), and 5.0% were obese (BMI ≥ 28.0 kg/m²). Demographic characteristics were collected solely to describe the sample and were not included as covariates in the network analysis.

2.2 Measures

2.2.1 Smartphone Addiction Scale–Short Version (SAS-SV)

Problematic smartphone use (PSU) was assessed using the Chinese version of the Smartphone Addiction Scale–Short Version (SAS-SV; Xiang et al., 2019). The scale consists of 10 items rated on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). An example item is, “I feel impatient and restless when my smartphone is not with me.” Higher scores indicate more severe problematic smartphone use. In the present sample, the scale demonstrated good internal consistency, with α = 0.916 and ω = 0.914 (see Table 1).

2.2.2 Bergen Social Media Addiction Scale (BSMAS)

Social media addiction was assessed using the Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2016). The scale consists of six items rated on a 5-point Likert scale ranging from 1 (*very rarely*) to 5 (*very often*). An example item is, “I use social media to escape from personal problems.” Higher scores indicate greater levels of social media dependence. In the present sample, α = 0.860 and ω = 0.864 (see Table 1).

2.2.3 Nine-Item Internet Gaming Disorder Scale–Short Form (IGDS9-SF)

Gaming disorder was assessed using the Nine-Item Internet Gaming Disorder Scale–Short Form (IGDS9-SF; Pontes & Griffiths, 2015). The scale consists of nine items rated on a 5-point Likert scale ranging from 1 (*never*) to 5 (*always*). An example item is, “Have you had difficulty resisting the temptation to play online games or difficulty stopping gaming?” Higher scores indicate greater severity of Internet gaming disorder. In the present sample, both α and ω were 0.924 (see Table 1).

2.2.4 Adolescent Health Related Risk Behavior Inventory (AHRBI)

Health-risk behaviors were assessed using the Adolescent Health Related Risk Behavior Inventory (AHRBI; Wang et al., 2012). The inventory originally consists of 38 items across six dimensions: suicide and self-harm, health-compromising behaviors, aggression and violence, rule-breaking behaviors, smoking and drinking, and unprotected sexual behavior. Items are rated on a 5-point Likert scale ranging from 0 (*never*) to 4 (*often*). Representative items for each dimension include: suicide and self-harm (“Have you ever attempted to cut or burn yourself?”); health-compromising behaviors (“Have you ever

engaged in binge eating or vomited after binge eating?"); aggression and violence ("Have you ever participated in a physical fight?"); rule-breaking behaviors ("Have you ever skipped classes or stayed away from school for an entire day?"); smoking and drinking ("Do you smoke?"); and unprotected sexual behavior ("Have you ever engaged in unsafe sexual behavior?"). Higher scores indicate more severe health-risk behaviors.

In the present sample, the total scale demonstrated good internal consistency (α = 0.915; ω = 0.915), and the α and ω coefficients for each dimension are presented in Table 1. Because the health-compromising behavior dimension demonstrated relatively low internal consistency, this dimension was excluded from the present study in accordance with previous research (Xie et al., 2013; Wang et al., 2012).

2.3 Statistical Analysis

Descriptive statistics were performed using SPSS 23.0. Network analyses, including cross-sectional network analysis, Bayesian network analysis, and computational intervention simulations, were conducted using R version 4.3.2. In network analysis, symptoms or behaviors are conceptualized as nodes within an interconnected system. By estimating statistical associations between nodes, network analysis allows the direct and indirect associations among multiple symptoms or behaviors to be examined simultaneously (Borsboom, 2017). In addition, directed acyclic graphs (DAGs) were used to preliminarily explore potential directional relationships among variables and to generate hypotheses regarding possible causal structures for future longitudinal research (McNally, 2016). Furthermore, the NodeIdentifyR algorithm was used to identify symptom-specific intervention targets that were expected to produce the greatest changes in the overall Ising network (Lunansky et al., 2022).

2.3.1 Network Analysis

The *bootnet* and *qgraph* packages in R were used to estimate and visualize the partial correlation network (Epskamp et al., 2012). The graphical least absolute shrinkage and selection operator (LASSO) was used to regularize the network estimation, with the extended Bayesian information criterion (EBIC) used to select the optimal network model (Friedman et al., 2008; Epskamp & Fried, 2018).

Edges in the network represent partial correlations between variables. Red edges indicate negative associations, whereas blue edges indicate positive associations. The thickness and color intensity of the edges represent the magnitude of the partial correlation coefficients. Node importance was assessed using expected influence (EI), which is calculated as the sum of the signed edge weights connected to a given node. Higher EI values indicate greater overall connectivity and potential influence within the network (Robinaugh et al., 2016). Bridge expected influence (BEI) was used to quantify the extent to which individual nodes connected the digital addiction and health-risk behavior communities. Larger absolute BEI values indicate stronger bridging roles between the two communities (Jones et al., 2019).

The stability of edge weights and centrality indices was assessed using 1,000 bootstrap resamples. A correlation stability coefficient greater than 0.5 was considered indicative of acceptable stability

(Epskamp et al., 2018).

2.3.2 Bayesian Network Analysis

A directed acyclic graph (DAG) was estimated using a Bayesian hill-climbing algorithm implemented in the *bnlearn* package (Scutari, 2010; Scutari & Denis, 2015), with the Bayesian information criterion (BIC) used to optimize model fit. Structural stability was assessed using 1,000 bootstrap resamples. The optimal cutoff method was used to retain edges with occurrence frequencies of ≥ 50% (Scutari & Nagarajan, 2013), and an edge direction was considered sufficiently supported when its direction probability was ≥ 50% (McNally et al., 2017).

In the DAG, arrows represent the estimated direction of statistical dependence, whereas the thickness of the edges represents the strength of the corresponding associations. Nodes positioned higher in the graph indicate higher hierarchical positions within the estimated network structure. Importantly, because the DAG analysis was based on cross-sectional data, the resulting structure represents directed statistical associations rather than confirmed causal relationships. The directions of the arrows should therefore be interpreted as data-driven statistical inferences and require further validation using longitudinal studies or experimental designs.

2.3.3 Computational Intervention Simulation

Computational network intervention simulations were conducted by constructing an Ising network model and using the *NodeIdentifyR* package in R (Lunansky et al., 2022). To simulate favorable and unfavorable states of individual nodes, the continuous variables were dichotomized according to their sample means. Values below the mean were coded as 0, representing a more favorable state of the corresponding node, whereas values above the mean were coded as 1, representing a less favorable state (Jiménez et al., 2023; Qi et al., 2025).

Using the NodeIdentifyR algorithm, 5,000 simulated participants were generated to evaluate two types of hypothetical node-level interventions within the Ising network. For the alleviating intervention, the original parameter value of a target node was decreased by two standard deviations to simulate an improvement in that node. For the aggravating intervention, the original parameter value was increased by two standard deviations to simulate a worsening of the corresponding node. The effects of interventions targeting each node were evaluated individually using the total network activation (sum score) as the outcome, allowing comparison of the relative impact of different node-specific perturbations on the overall network state (Dalege et al., 2017).

3 Results

3.1 Descriptive Statistics and Reliability

The means, standard deviations, and reliability coefficients for the dimensions of digital addiction and health-risk behaviors are presented in Table 1. Among the digital addiction-related variables, problematic

smartphone use (PSU) had the highest mean score. Among the health-risk behavior variables, smoking and drinking had the highest mean score, whereas unprotected sexual behavior had the lowest mean score.

Table 1
Means, standard deviations, and reliability coefficients of digital addiction and health-risk behavior dimensions

Variable	Scale	α	ω	*M*	*SD*
DA	BSMAS	0.860	0.864	2.227	0.686
	IGDS9-SF	0.924	0.924	1.681	0.710
	SAS-SV	0.916	0.914	3.165	0.964
AHRBI	SS	0.859	0.866	0.257	0.508
	AV	0.799	0.750	0.322	0.337
	RB	0.755	0.716	0.364	0.412
	SD	0.779	0.753	0.378	0.551
	US	0.800	0.821	0.063	0.252

Note: SS: Suicide and Self-harm; AV: Aggressive and Violent Behavior; RB: Rule-breaking behaviors; SD: Smoking and Drinking; US: Unprotected Sexual Behavior.

3.2 Network Structure and Simulated Intervention Targets Linking Digital Addiction to Health-Risk Behaviors in University Students

3.2.1 Network Estimation

Table S1 presents the descriptive statistics for digital addiction and health-risk behaviors, as well as the proportions of participants classified as having active symptoms for each node in the Ising network. The estimated network consisted of eight nodes and 27 non-zero edges (Fig. 1). Among these, 14 edges connected nodes across the two communities. However, the absolute weights of the cross-community edges were generally small (|edge weight| ≤ 0.112), indicating that although statistically detectable associations existed between digital addiction and health-risk behaviors, the magnitude of these cross-community associations was generally small to moderate.

3.2.2 Centrality and Stability Estimation

As shown in Fig. 2, aggression and violence had the highest expected influence (EI = 1.582), followed by rule-breaking behaviors (EI = 1.510), indicating that these two nodes were the most strongly connected to the overall network structure. Among the bridge nodes connecting the digital addiction and health-risk

behavior communities, gaming disorder had the highest bridge expected influence (BEI = 0.245), followed by aggression and violence (BEI = 0.192).

The accuracy and stability analyses (see Supplementary Figures S1–S3) showed relatively narrow 95% confidence intervals, indicating good precision of the edge-weight estimates. Both EI and BEI demonstrated a correlation stability (CS) coefficient of 0.75, indicating good overall stability of the centrality estimates.

3.3 Bayesian Network and Directed Acyclic Graph (DAG) Results

Figure 3 presents the directed acyclic graph (DAG) of digital addiction and health-risk behaviors estimated using Bayesian network analysis. In Fig. 3A, edge thickness represents the contribution of each edge to the overall model fit, quantified by the change in the Bayesian information criterion (BIC) after removing the corresponding edge (Blanchard et al., 2021). Thicker edges indicate a greater contribution to model fit. In the present study, the strongest contributions to model fit were observed for the directed edge from aggression and violence to rule-breaking behaviors (BIC = − 734.89) and the directed edge from social media addiction to problematic smartphone use (BIC = − 368.11).

In Fig. 3B, arrow thickness represents the probability of a particular edge direction, defined as the proportion of bootstrap DAGs in which an edge appeared in the specified direction (Heeren et al., 2020). Among the 2,000 bootstrap DAGs, the strongest directional support was observed for the edge from aggression and violence to unprotected sexual behavior (proportion = 0.880), followed by the edge from aggression and violence to suicide and self-harm (proportion = 0.875).

Structurally, social media addiction (SMA) occupied a relatively high hierarchical position in the network and showed directed associations with problematic smartphone use (PSU), gaming disorder (GD), and aggression and violence (AV). Importantly, the DAG results represent directed statistical associations among variables, and the estimated directions should not be interpreted as evidence of causal relationships. Further longitudinal or experimental research is required to determine whether these directional associations reflect underlying causal processes.

(A) Edge thickness represents the contribution of each edge to model fitting; (B) arrow thickness represents the probability of edge direction.

3.4 Results of the Computational Intervention Simulation

Figure 4 presents the results of the network intervention analysis (NIRA). Figure 4A shows the results of the alleviating intervention, in which each node was simulated to perform more favorably. The results indicated that improving the rule-breaking behaviors node produced the largest reduction in overall network activation, with the mean activation level decreasing from 2.90 to 1.98 (95% CI [1.93, 2.03]; see Table S2). Figure 4B shows the results of the aggravating intervention, in which each node was

simulated to perform more negatively. Worsening the aggression and violence node produced the largest increase in overall network activation, from 2.90 to 4.06 (95% CI [4.00, 4.12]; see Table S3).

To further examine whether the simulated intervention effects differed significantly across target nodes, pairwise comparisons were conducted among the intervention effects for all nodes, with Bonferroni correction applied for multiple comparisons (Tables S4 and S5). For the alleviating interventions, several pairwise comparisons involving rule-breaking behaviors showed relatively large differences in effect size; however, the difference between rule-breaking behaviors and aggression and violent behaviors did not reach statistical significance (p = .078). For the aggravating interventions, aggression and violent behaviors produced the largest increase in overall network activation, but its effects did not differ significantly from those of rule-breaking behaviors or other high-effect nodes. Therefore, although rule-breaking behaviors and aggression and violent behaviors showed the largest simulated effects for alleviating and aggravating interventions, respectively, the present results do not provide sufficient evidence that interventions targeting either node would produce significantly greater effects than interventions targeting other nodes.

(A) Alleviating interventions; (B) aggravating interventions.

4 Discussion

The present study used a network approach to systematically examine the interrelationships between digital addiction and health-risk behaviors among Chinese university students. Three main findings emerged. First, aggression and violence had the highest expected influence (EI = 1.582) and a relatively high bridge expected influence (BEI = 0.192), indicating an important structural position in the network and its connections between digital addiction and health-risk behaviors. Second, social media addiction appeared to occupy a relatively high hierarchical position in the estimated Bayesian network. Third, computational intervention simulations indicated that reducing rule-breaking behaviors produced the largest reduction in overall network activation, whereas increasing aggression and violence produced the largest increase. However, pairwise comparisons showed that the differences between the leading nodes were not uniformly statistically significant. Therefore, these findings should be interpreted as potential intervention-relevant signals based on the observed network structure rather than as evidence of validated or superior intervention targets.

4.1 Aggression and Violence as a Central and Bridging Node

Aggression and violence showed the highest expected influence and a relatively high bridge expected influence in the present network, suggesting that this domain may occupy an important structural position both within the overall network and in linking digital addiction with health-risk behaviors. From a network perspective, highly central nodes may be more closely connected to multiple other nodes, such that changes in their activation may be associated with changes in other parts of the network (Hofmann

et al., 2016). However, given the cross-sectional nature of the present study, the centrality of aggression and violence should be interpreted as reflecting the strength of statistical associations rather than evidence that aggression and violence causally drive other health-risk behaviors.

The finding is broadly consistent with previous evidence linking digital technology use and aggression. A meta-analysis has reported a moderate positive association between Internet gaming disorder and aggression (Li et al., 2023). From the perspective of social learning theory, aggressive behaviors can be acquired through observation and imitation, while repeated exposure to violent content and competitive interactions may provide opportunities for learning aggressive responses (Bandura, 1977). Reward contingencies may further reinforce such behavioral patterns. Thus, sustained engagement with highly stimulating digital environments may be associated with the activation and reinforcement of aggressive cognitions and behavioral tendencies, which may help explain why aggression and violence occupied a prominent position in the present network.

The relatively high bridge expected influence of aggression and violence is also noteworthy. Digital environments may involve exposure to violent content, interpersonal conflict, or competitive interactions, which may be associated with aggressive cognitions and emotional arousal. The General Aggression Model proposes that repeated exposure to aggressive cues can influence aggressive cognition, affect, and behavioral responses, thereby increasing the likelihood of aggressive behavior under relevant circumstances (Anderson & Bushman, 2002; Anderson et al., 2010; Bushman & Huesmann, 2006). From this perspective, aggression and violence may represent a behavioral domain through which digital addiction and other health-risk behaviors are statistically interconnected. Nevertheless, the present network cannot determine whether digital addiction leads to aggression, whether aggression increases vulnerability to digital addiction, or whether both are influenced by unmeasured third variables.

4.2 The Potential Hierarchical Position of Social Media Addiction

The Bayesian network analysis indicated that social media addiction occupied a relatively high hierarchical position in the estimated network structure and showed directed statistical associations with problematic smartphone use, gaming disorder, and aggression and violence. This finding suggests that social media addiction may be particularly embedded within the broader network of digital addiction and health-risk behaviors. Previous research has linked problematic social media use to attentional involvement and sleep problems (Kuss & Griffiths, 2017; Valkenburg et al., 2022), which may contribute to broader patterns of psychological and behavioral difficulties.

Problematic social media use may also be associated with loneliness and reduced social functioning. Previous research suggests that problematic social media use can be involved in a reciprocal pattern in which greater use is associated with greater loneliness, while reduced real-world social support may in turn encourage further online engagement (Błachnio & Przepiorka, 2019). Social media platforms also have a relatively low threshold for repeated engagement and can continuously capture users' attention through fragmented and highly accessible digital stimuli (Eyal, 2014; Kuss & Griffiths, 2017). These

characteristics may make problematic use particularly relevant to university students, who frequently rely on digital platforms for both social interaction and everyday communication.

The association between social media use and health-risk behaviors also provides a possible context for understanding its position in the present network. Recent evidence has reported associations between social media use and health-risk behaviors, including smoking, alcohol use, and substance-related behaviors (Yang et al., 2025). Taken together, these findings suggest that social media addiction may occupy an important position within the broader behavioral network. However, the directionality identified by the Bayesian network should be interpreted cautiously. Because the analysis was based on cross-sectional data, the estimated directions represent data-driven statistical dependencies rather than established causal pathways.

4.3 Interpretation of the Computational Intervention Simulations

The computational intervention simulations provided additional model-based information regarding the potential network-level consequences of changing individual nodes. In the alleviating simulation, reducing rule-breaking behaviors by two standard deviations produced the largest decrease in overall network activation. In the aggravating simulation, increasing aggression and violence by two standard deviations produced the largest increase in overall network activation. These findings indicate that altering the simulated states of these nodes was associated with relatively large changes in the predicted overall network activation under the specified Ising model.

The relatively large alleviating effect associated with rule-breaking behaviors may be understood in the context of Problem Behavior Theory, which conceptualizes rule-breaking behaviors, aggression, substance use, and other health-risk behaviors as interconnected components of a broader problem-behavior syndrome (Donovan & Jessor, 1985; Jessor, 1991). Within such a system, rule-breaking behaviors behaviors may be statistically connected with multiple forms of health-risk behavior. Consequently, reducing the activation of rule-breaking behaviors may produce broader changes in the modeled network rather than affecting rule-breaking behaviors alone. This interpretation is consistent with the network-level nature of the simulation, but it should not be interpreted as evidence that interventions targeting rule-breaking behaviors would necessarily produce equivalent effects in real-world settings.

Aggression and violence showed the largest simulated increase in overall network activation under the aggravating condition. This result is compatible with the central and bridging position of aggression and violence identified in the network analysis. The General Aggression Model and social learning theory provide plausible theoretical contexts for understanding why aggression may be closely connected with other behavioral problems (Bandura, 1977; Anderson & Bushman, 2002; Anderson et al., 2010). Nevertheless, the simulated increase reflects a model-based perturbation rather than an experimentally induced behavioral change. Therefore, it cannot be interpreted as evidence that increasing aggression and violence would causally increase other health-risk behaviors.

Importantly, pairwise comparisons of simulated intervention effects showed that the apparent advantage of the leading nodes was not consistently statistically significant. In particular, the difference between rule-breaking behaviors and aggression and violent behaviors in the alleviating condition did not reach statistical significance (p = .078), and aggression and violent behaviors did not differ significantly from rule-breaking behaviors or other high-effect nodes in the aggravating condition. Thus, although rule-breaking behaviors and aggression and violent behaviors produced relatively large simulated effects, the evidence does not support the conclusion that either node has a uniquely or significantly greater intervention effect than the other nodes. This distinction is important because a node producing the largest point estimate in a simulation should not automatically be interpreted as a superior intervention target. Rather, the present findings indicate that rule-breaking behaviors and aggression and violent behaviors are prominent candidate nodes within the current network structure whose alteration was associated with comparatively large model-predicted changes in network activation.

4.4 Limitations

Several limitations should be considered when interpreting the present findings. First, the computational intervention simulations were based on cross-sectional data and therefore cannot provide evidence of the actual effectiveness of interventions in real-world settings. Second, the simulations focused on perturbing one node at a time. Given the interdependent nature of symptoms and behaviors, simultaneous perturbation of multiple nodes may yield different network-level effects and may provide a more comprehensive representation of potential intervention strategies (Lunansky et al., 2022). Third, all variables were assessed using self-report questionnaires, which may be subject to recall errors, social desirability, and other response biases. Finally, the computational intervention analysis required continuous variables to be dichotomized using the sample mean as the threshold. Although this procedure was consistent with the analytical framework of the Ising model and NIRA, dichotomization may result in information loss and potential misclassification of individuals whose scores are close to the threshold. Future studies may consider clinically or theoretically informed cutoffs, where appropriate, or ordinal network models (e.g., multinomial Ising models) to retain more information from the original scale scores and obtain more nuanced estimates.

5 Conclusion

Overall, the present study used an Ising network model, Bayesian network analysis, and network intervention analysis to examine the relationships between digital addiction and health-risk behaviors among Chinese university students. Aggression and violence showed the highest expected influence and a relatively strong bridging role, indicating an important structural position within the network connecting digital addiction and health-risk behaviors. Social media addiction occupied a relatively high hierarchical position in the estimated Bayesian network, although the identified directions represent statistical dependencies rather than established causal relationships. Computational intervention simulations indicated that reducing rule-breaking behaviors produced the largest decrease in overall network activation, whereas increasing aggression and violence produced the largest increase. However, pairwise

comparisons did not demonstrate statistically significant differences between the leading nodes across all comparisons. Therefore, rule-breaking behaviors and aggression and violent behaviors should be regarded as nodes associated with relatively large model-based simulated effects within the present network, rather than as uniquely superior or empirically validated intervention targets.

Declarations

Ethics approval and consent to participate

This study was conducted in accordance with the Declaration of Helsinki. The research protocol has been approved by the Ethics Committee of the School of Psychology at Northwest Normal University. All participants and guardians provided their informed consent by signing the consent form prior to participating in the survey.

Written informed consent was obtained from all participants.

Consent for publication

Not applicable.

Trial Registration

Not applicable.

Availability of data and materials

The datasets generated and/or analyzed during the current study are not publicly available due to ethical restrictions concerning the confidentiality of the human participants. However, they are available from the corresponding author, Xiangling Tu, upon reasonable request. Requests for data access should be directed to 363246121@qq.com

Competing interests

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Authors' contributions

WB: conceptualization, methodology, formal analysis, writing– original draft. **CM**: investigation, conceptualization, supervision, project administration. **TXL**: methodology, software, writing–review and editing. **ZJC**: methodology, software.

FYX: data collection, data curation. All authors read and approved the final manuscript.

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Data Availability Statement

The datasets generated and/or analyzed during the current study are available as supplementary files in the submission system. The raw data and processed data have been provided for peer review purposes. The data dictionary, including variable definitions, coding schemes, and calculation formulas, is also included as a supplementary file. The complete questionnaires (Chinese version) are provided in the Supplementary Information. All materials are fully anonymized. Analysis scripts and code are available from the corresponding author upon reasonable request. No third-party data or proprietary materials were used in this study.

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Figures

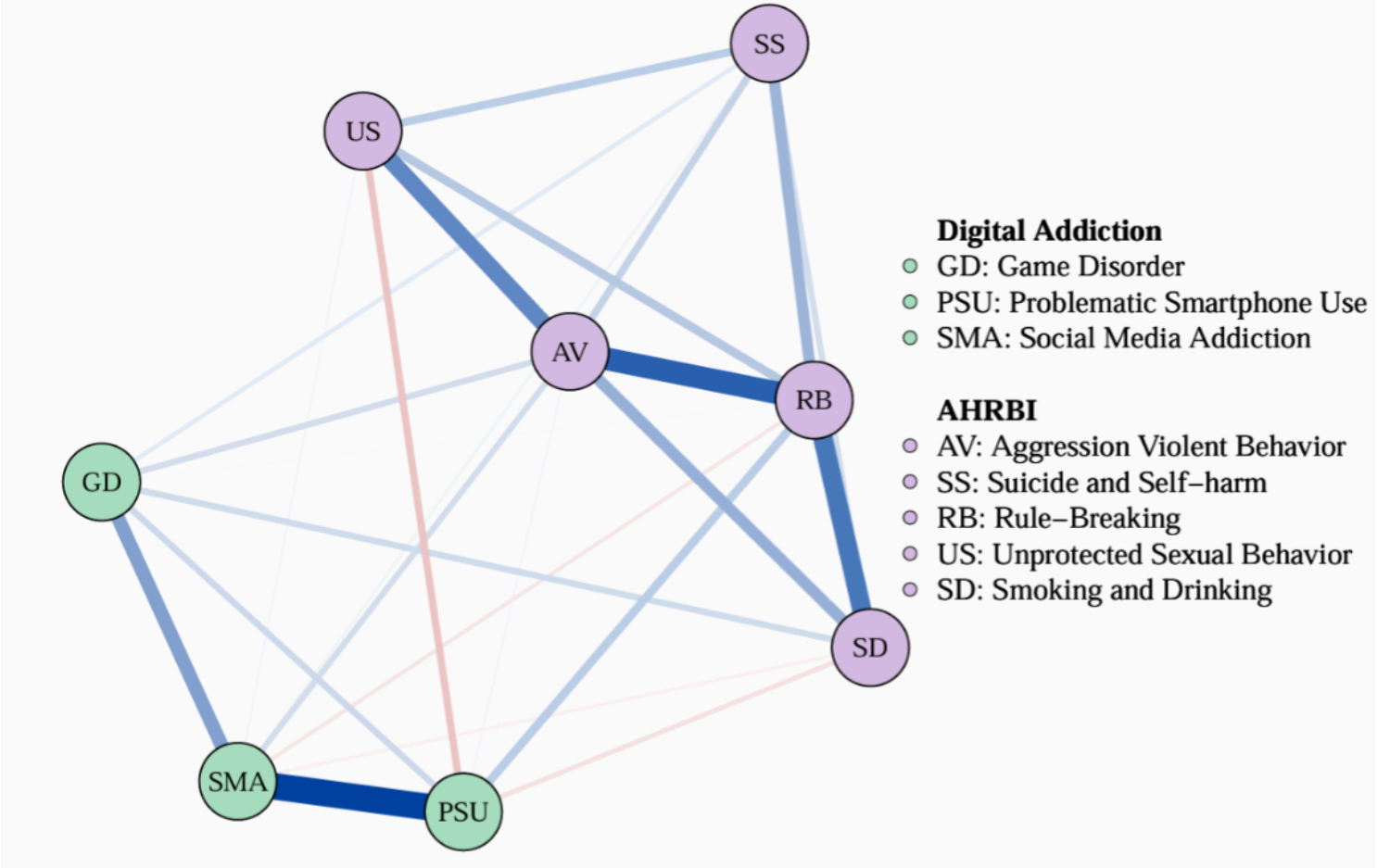


Figure 1

Network structure of digital addiction and health risk behaviors

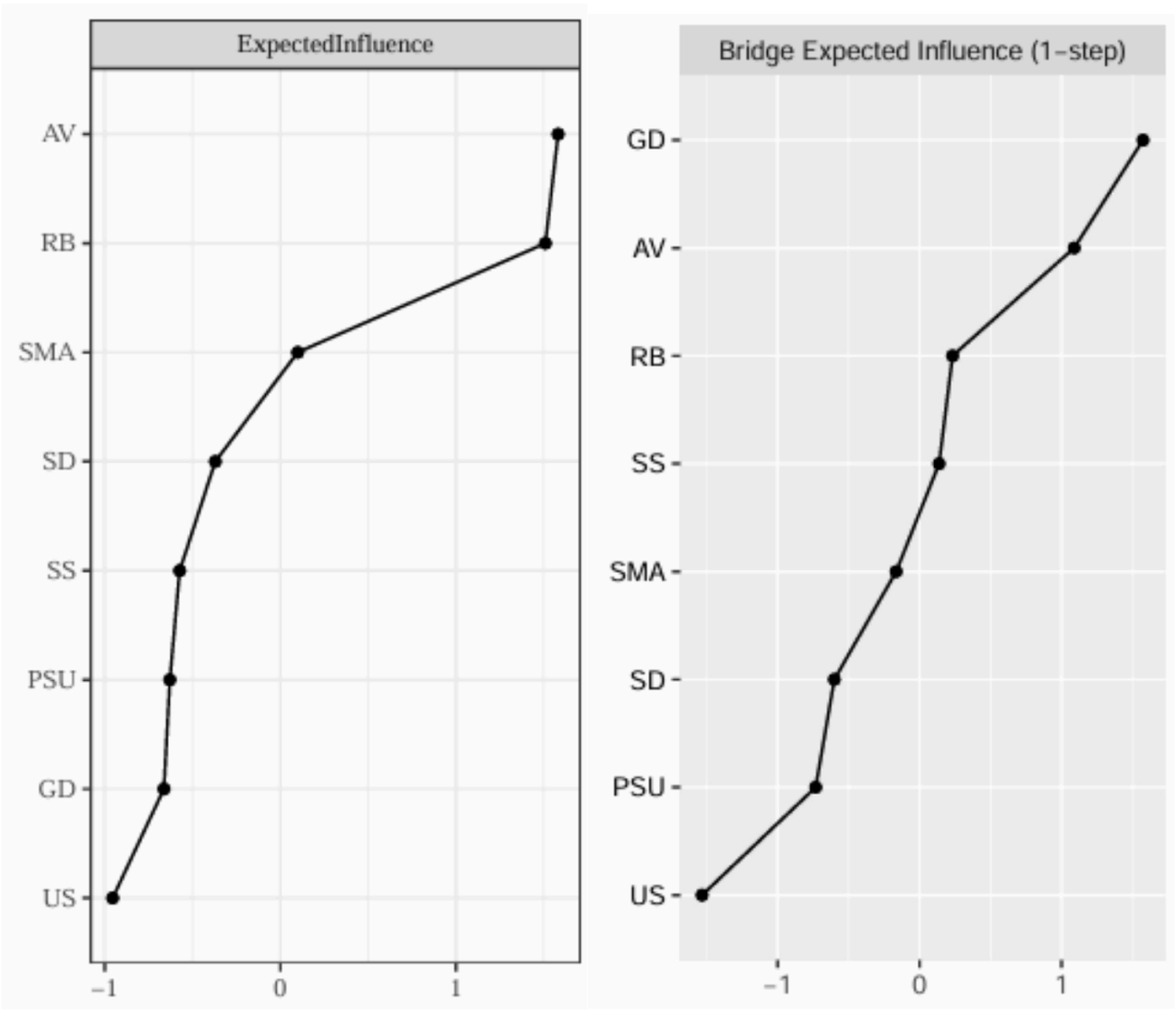


Figure 2

Centrality of nodes in the network structure of digital addiction and health risk behaviors

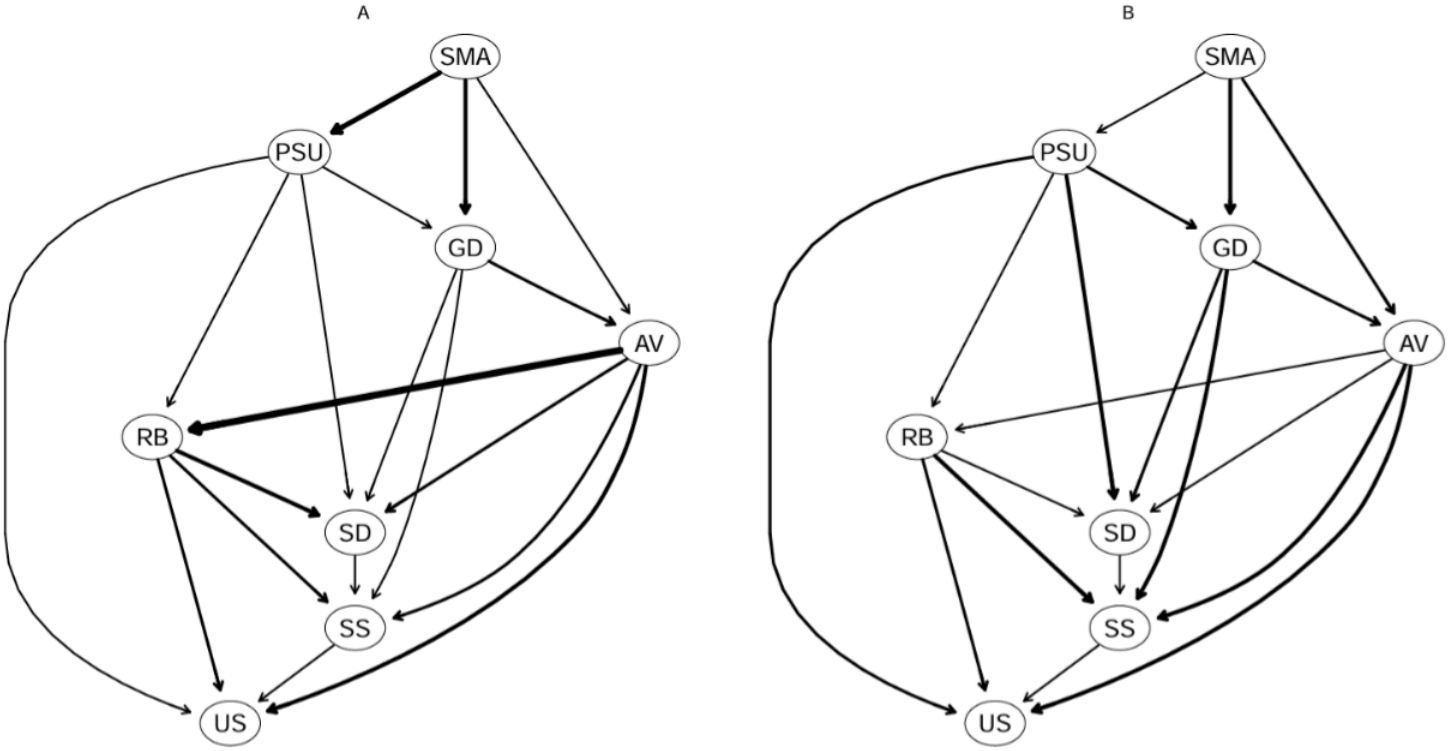


Figure 3

Directed acyclic graph of digital addiction and health risk behaviors.

(A) Edge thickness represents the contribution of each edge to model fitting; (B) arrow thickness represents the probability of edge direction.

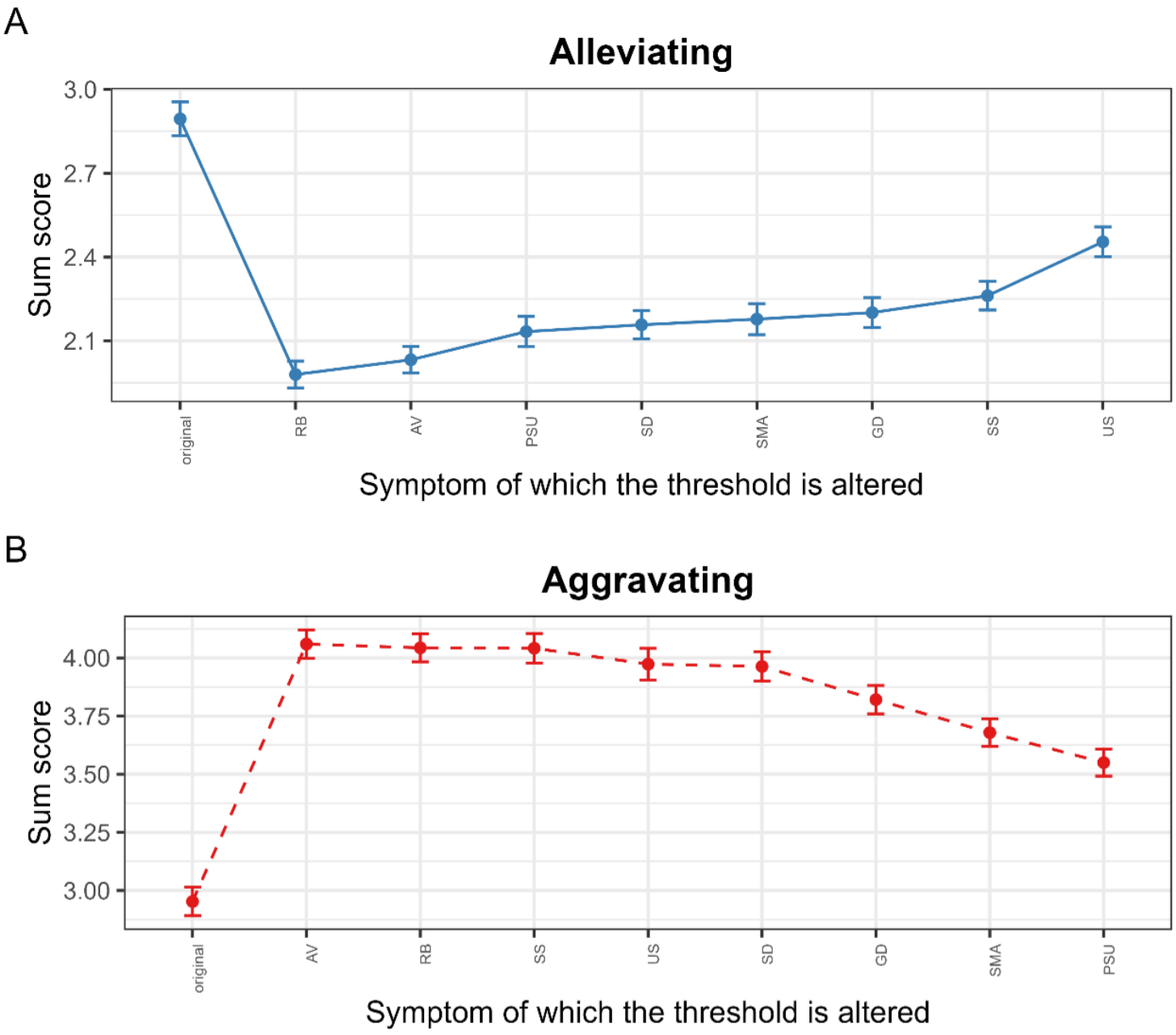


Figure 4

Results of computational simulation interventions based on network analysis.

(A) Alleviating interventions; (B) aggravating interventions.

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