

The relationship between growth mindset and short-video addiction among nursing students: Serial mediation and simulation-based network analysis

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Abstract

Background

Short-video addiction is a relevant concern for nursing students' well-being and academic performance. Positive psychological resources may be protective, but evidence linking growth mindset to short-video addiction through resilience and general self-efficacy remains limited. This study examined whether resilience and general self-efficacy mediate the association between growth mindset and short-video addiction, and identified specific items with the strongest connectivity or simulated network responsiveness using item-level network analysis.

Methods

This cross-sectional survey included a convenience sample of 1,041 nursing students from a nursing college in southern China, surveyed from July 3 to August 20, 2026. PROCESS Model 6 tested serial mediation with 5,000 bootstrap resamples, 95% percentile confidence interval, and adjustment for prespecified covariates. An Ising network estimated expected influence (EI) and bridge expected influence (BEI); NodelIdentifyR algorithm (NIRA) simulations shifted each node's threshold by ± 2 standard deviations. The network sum score was defined as the model-estimated total expected activation across all 55 binary item nodes.

Results

Growth mindset showed a negative total association with short-video addiction ($\beta = -0.317$, 95% CI -0.374 to -0.259); the direct association was -0.214 (95% CI -0.269 to -0.159). The total indirect association was -0.103 (95% CI -0.130 to -0.077), comprising pathways through resilience (-0.059 , 95% CI -0.080 to -0.040), general self-efficacy (-0.031 , 95% CI -0.047 to -0.019), and their serial pathway (-0.012 , 95% CI -0.018 to -0.007). Based on point estimates, K24 ("Persistence despite obstacles") had the highest EI (8.394), and Z10 ("Confidence in problem solving") had the highest BEI (4.193). From a baseline network sum score of 18.447, the K13 ("Awareness of support resources") -2SD corresponded to 17.372 (change -1.074 , 99.91% CI 0.739 to 1.381), and the Z10 + 2SD corresponded to 19.943 (change $+1.496$, 99.91% CI 1.146 to 1.833).

Conclusions

In this study, resilience and general self-efficacy may mark statistical pathways linking growth mindset to short-video addiction. K24 ("Persistence despite obstacles"), Z10 ("Confidence in problem solving"), and K13 ("Awareness of support resources") may be relevant to understanding the relationship between short-video addiction and positive psychological resources among nursing students, and may help

prioritize targets for further longitudinal or experimental investigation; the cross-sectional and simulation findings do not establish causal or intervention effects.

1. Background

Nursing students are an important part of the future healthcare workforce. Their training combines demanding coursework^[1] with clinical learning^[2], where they encounter cognitive demands and emotionally challenging situations^[3]. Short videos are now a common part of university students' daily lives. Their fragmented content, immediate feedback, and personalized recommendations can encourage repeated use^[4, 5]. By December 2025, China had 1.074 billion short-video users, accounting for 95.4% of all internet users^[6]. For some nursing students, short videos may offer a readily available way to shift attention away from unpleasant feelings^[5]. Use is not necessarily problematic, but prolonged and difficult-to-control use that interferes with learning, sleep, or social functioning may be considered problematic short-video use or short-video addiction tendency^[4, 7].

Short-video addiction refers here to difficulty controlling short-video use, together with excessive involvement, withdrawal-like discomfort, and impairment in daily functioning. It is not currently a formal psychiatric diagnosis; in this study, the term denotes a tendency measured by a standardized questionnaire rather than a clinical disorder. A recent study reported a screening-positive rate of 31.3% among nursing students in China^[8]. Short-video addiction has also been associated with inattention among undergraduate nursing students^[9] and with learning motivation, well-being, and related outcomes in other student samples^[10]. These findings make short-video use a relevant behavioral correlate to examine in nursing students. Social-media use and psychological distress have also been discussed in reviews of undergraduate nursing students^[11]. Yet evidence on the psychological factors associated with short-video addiction remains limited, particularly for positive cognitive beliefs and psychological resources.

The Interaction of Person-Affect-Cognition-Execution (I-PACE) model suggests that problematic digital-media use is influenced by individual characteristics, emotional and cognitive responses, and self-control processes^[12]. Positive cognitive beliefs may shape how students respond to academic stress and negative emotions. Students who view difficulties as manageable may be less likely to use short videos to escape distress or obtain immediate relief. Growth mindset is the belief that one's abilities can develop through effort, effective strategies, and learning from experience^[13, 14]. Students who hold this belief tend to interpret difficulties as problems that can be worked on and are more likely to persist or adjust their strategies. This orientation may be relevant to problematic digital-media use, although findings across populations and media behaviors have not been consistent^[15]. Direct evidence on growth mindset and short-video addiction is still limited, especially among nursing students.

The association between growth mindset and short-video addiction may therefore involve psychological adaptation rather than a single direct link. Resilience refers to the capacity to maintain or regain adaptive

functioning after adversity^[16]. A growth mindset may be associated with resilience because students who view abilities as changeable are more likely to persist when difficulties arise and to revise their approach after setbacks. In turn, students with greater resilience may be less likely to use short videos as a way of escaping unpleasant feelings or obtaining immediate relief. Previous research has reported an inverse association between resilience and short-video addiction^[17]. Resilience was therefore considered a possible mediator of the association between growth mindset and short-video addiction.

Resilience may also be related to short-video addiction through general self-efficacy. General self-efficacy is a person's overall judgment that they can cope with difficult situations and accomplish required tasks^[18, 19]. Repeated experiences of handling setbacks and returning to effective functioning may strengthen this judgment. Among nursing students, academic self-efficacy has been associated with a lower risk of social-media addiction^[20], and self-efficacy has been inversely related to problematic internet use^[21]. Growth mindset has also been positively associated with self-efficacy-related outcomes among Chinese nurses^[22]. These findings provide a basis for examining the two psychological resources within one model, although most previous studies have considered them separately or examined only pairs of variables.

The proposed order follows a conceptual distinction between resilience and general self-efficacy. Resilience concerns how a person adapts and recovers when difficulties occur, whereas general self-efficacy concerns the subsequent appraisal of personal capability. Growth mindset may therefore be associated with resilient responses to difficulty; these experiences may in turn be related to general self-efficacy, which may be associated with lower short-video addiction. This model can be situated within the I-PACE framework, which describes problematic digital-media use as emerging from the interplay of individual characteristics, affective and cognitive processes, and executive processes^[12].

In this study, growth mindset was treated as an individual cognitive belief. Resilience and general self-efficacy were examined as psychological resources involved in adaptation and self-appraisal, while short-video addiction was treated as the behavioral outcome. These mappings were used to organize the hypotheses rather than to claim that the measured variables represent every component of the I-PACE model. We proposed the following hypotheses:

H1: Growth mindset is negatively associated with short-video addiction among nursing students.

H2: Resilience mediates the association between growth mindset and short-video addiction.

H3: General self-efficacy mediates the association between growth mindset and short-video addiction.

H4: Growth mindset is indirectly associated with short-video addiction through the serial pathway of resilience → general self-efficacy.

The hypotheses concern associations among four constructs, whereas the mediation analysis uses their total scale scores. Total scores are useful for estimating construct-level relationships but do not show

which individual item contents are most closely connected. Items within one scale may represent different experiences and may link with items from another construct in different ways. An item-level analysis was therefore needed to complement the total-score model.

We used psychometric network analysis to examine conditional associations among the 55 items. The network represents items as nodes and conditional associations as edges, allowing within- and between-construct connections to be examined^[23]. Centrality and bridge indices describe different forms of connectivity, but they do not estimate how the overall network score would respond to a change in one node.

We therefore applied the NodeIdentifyR algorithm (NIRA)^[24]. NIRA perturbs a node threshold in the fitted network and evaluates the resulting model-implied change in the network sum score. It identifies nodes associated with larger simulated responses under the specified perturbation, rather than estimating an observed intervention effect. Network analysis and NIRA thus provide complementary descriptions of item connectivity and model-implied response.

This study examined the association between growth mindset and short-video addiction among nursing students, including the specific and serial indirect associations through resilience and general self-efficacy. We combined construct-level mediation analysis with item-level Ising network analysis and threshold-perturbation simulations to examine the same research question at two levels of analysis.

2. Methods

This cross-sectional study was conducted and reported in accordance with the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist for cross-sectional studies.

2.1 Participants

This study employed a cross-sectional questionnaire survey with a convenience sampling method. The survey was conducted from July 3 to August 20, 2026 at a nursing college in Guangdong Province, China. The research team distributed the questionnaire link and QR code through class group chats on WeChat via student leaders, and data were collected online using the Wenjuanxing platform.

Inclusion criteria were: (1) full-time undergraduate or diploma nursing students; (2) using short-video applications for at least 30 minutes per day with a frequency of no less than twice daily^[25]; and (3) voluntary participation with signed informed consent. Exclusion criteria were: (1) a documented history of psychiatric or cognitive disorders; (2) self-reported exposure to major psychological trauma or stressful events within the past three months; and (3) current participation in other similar studies.

A total of 1,069 completed questionnaires were received. All items were set as mandatory on the Wenjuanxing platform, and participants could only submit the questionnaire after completing all items; thus, no missing data were present in the returned responses. After data quality screening, 28

questionnaires were excluded, including 19 with obvious patterned responses or logical inconsistencies, and 9 that failed the attention check items. The final analytic sample consisted of 1,041 nursing students, yielding a retention rate of 97.38%.

2.2 Sample size calculation

A priori sample size estimation was performed to accommodate both the serial mediation model and the item-level binary network analyses. For the serial mediation model, a Monte Carlo power simulation was conducted following the approach of Schoemann et al., with a two-sided alpha level of 0.05, a desired power of 0.80, and assuming standardized path coefficients with absolute values not less than 0.30 (i.e., medium effect sizes)^[26]. The simulation results indicated that a minimum of 240 participants would be required.

For the network analysis, previous simulation studies have suggested that low-to-moderate sized networks containing 10–30 nodes based on binary data typically require approximately 500 observations, whereas larger networks with up to 100 nodes may require around 1,000 participants^[27]. The Ising network in the present study comprised 55 binary nodes, exceeding the scale of the aforementioned moderate networks. Therefore, a conservative target sample size of 1,000 was set to ensure stability in edge weight estimation and centrality ranking. Integrating the sample size requirements of both analytic approaches, the larger target of 1,000 participants was adopted as the overall minimum sample size. The final sample of 1,041 eligible participants met this requirement.

2.3 Measures

2.3.1 General information questionnaire

A demographic questionnaire was developed by the research team, informed by prior studies on psychological adaptation and problematic short-video use among nursing students, as well as the characteristics of nursing education and clinical practice. The questionnaire covered: demographic characteristics (age, gender, ethnicity, and place of household registration), education and training-related characteristics (level of education, year of study, and whether clinical internship had commenced), and characteristics related to program choice (whether nursing was a voluntary choice and whether it was the first-choice major).

2.3.2 Growth Mindset Scale

Growth mindset was assessed using the Chinese version of the 6-item Growth Mindset Scale (GMS), originally developed by Dweck^[14] and subsequently translated and validated in Chinese populations^[28]. This Chinese version has demonstrated good reliability in previous studies, with Cronbach's α values ranging from 0.81 to 0.87. Each item is rated on a 6-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree), with items C1, C2, and C3 reverse-coded. The total score is calculated by summing all item responses, yielding a possible range of 6 to 36, with higher scores reflecting a stronger growth

mindset. In this sample, the GMS demonstrated acceptable internal consistency, with a Cronbach's α of 0.74.

2.3.3 Short Video Addiction Scale

Short-video addiction was assessed using the 14-item Short Video Addiction Scale (SVAS), developed by Qin^[29]. Previous studies have reported good reliability for this scale, with a Cronbach's α of 0.91. Items are rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). All items are positively worded, and total scores are calculated by summing all item responses, yielding a possible range of 14 to 70, with higher scores indicating greater addiction tendency. In this sample, the SVAS demonstrated good internal consistency, with a Cronbach's α of 0.85.

2.3.4 Connor-Davidson Resilience Scale

Resilience was assessed using the 25-item Connor-Davidson Resilience Scale (CD-RISC), originally developed by Connor and Davidson^[16]. The Chinese version of this scale has demonstrated good reliability in previous studies, with a Cronbach's α of 0.91^[30]. Items are rated on a 5-point frequency scale ranging from 0 (never) to 4 (almost always). Total scores are calculated by summing all item responses, yielding a possible range of 0 to 100, with higher scores indicating greater resilience. In this sample, the CD-RISC demonstrated good internal consistency, with a Cronbach's α of 0.89.

2.3.5 General Self-Efficacy Scale

General self-efficacy was assessed using the 10-item General Self-Efficacy Scale (GSES), originally developed by Schwarzer and Jerusalem^[18]. The Chinese version of this scale has demonstrated good reliability in previous studies, with a Cronbach's α of 0.87^[19]. Items are rated on a 4-point scale ranging from 1 (not at all true) to 4 (exactly true). Total scores are calculated by summing all item responses, yielding a possible range of 10 to 40, with higher scores indicating greater general self-efficacy. In this sample, the GSES demonstrated a Cronbach's α of 0.73.

2.4 Data analysis

2.4.1 Descriptive statistics and associations

The distribution of continuous variables was examined with the Shapiro–Wilk test (Supplementary Table 1). Continuous variables with non-normal distributions are reported as medians and interquartile ranges, and categorical variables as frequencies and percentages. Spearman rank correlations were used to describe bivariate associations among total scale scores. Cronbach's alpha was calculated to summarize internal consistency. Multicollinearity among predictors in the mediation model was assessed with the generalized variance inflation factor (GVIF); for categorical predictors with more than one degree of freedom, the adjusted index $GVIF^{(1/(2 \times Df))}$ was reported (Supplementary Table 2).

2.4.2 Serial mediation analysis

The serial multiple mediation model was estimated using Model 6 of the PROCESS macro. Growth mindset was specified as the independent variable (X), short-video addiction as the dependent variable (Y), and resilience and general self-efficacy as the first (M_1) and second (M_2) mediators, respectively, with the hypothesized serial pathway following the order: growth mindset → resilience → general self-efficacy → short-video addiction. All four constructs were entered as observed variables using their respective total scale scores. The model adjusted for age, gender, ethnicity, place of household registration, level of education, year of study, whether nursing was a voluntary choice, whether nursing was the first-choice major, and whether clinical internship had commenced, with coding details provided in Supplementary Table 3. Regression coefficients were estimated using HC3 heteroskedasticity-consistent standard errors, and 95% percentile confidence interval for each specific indirect effect and the total indirect effect were obtained through 5,000 bootstrap resamples. An indirect effect was considered statistically meaningful if its 95% confidence interval did not contain zero.

2.4.3 Ising network estimation and NIRA simulations of threshold perturbations

The Ising model requires binary input variables (The encoded response distributions are provided in Supplementary Table 4)^[31]; accordingly, the 55 items were dichotomized based on the semantic meaning of the response options^[32, 33]. For the Growth Mindset Scale, items C1–C3 were first reverse-coded to ensure consistent scoring direction across all items. Responses of 1–3 were then coded as 0, and responses of 4–6 were coded as 1, representing disagreement and agreement with the respective item, respectively. For the Short Video Addiction Scale, responses of 1–3 were coded as 0, and responses of 4–5 were coded as 1, indicating non-endorsement and endorsement of the corresponding addictive manifestations, respectively. For the Connor-Davidson Resilience Scale, responses of 0–1 were coded as 0, and responses of 2–4 were coded as 1, indicating that the corresponding psychological or behavioral manifestations were absent or rarely present versus present at least sometimes, respectively. For the General Self-Efficacy Scale, responses of 1–2 were coded as 0, and responses of 3–4 were coded as 1, indicating lower and higher endorsement of the corresponding ability judgments, respectively. Thus, a code of 1 consistently indicated higher levels of the trait described by the item: for growth mindset, resilience, and general self-efficacy items, higher scores represented adaptive psychological characteristics; for short-video addiction items, higher scores represented addiction-related manifestations.

The Ising network was estimated using the IsingFit package in R 4.6.1 via L1-regularized logistic regression^[34]. Model selection was guided by the extended Bayesian information criterion (EBIC; $\gamma = 0.25$), and network edges were retained based on the AND rule. Networks were visualized using the qgraph package, with edge colors representing the direction of associations (green for positive, red for negative) and edge thickness representing association strength. Node strength and expected influence (EI) were used to describe overall connectivity^[35]; bridge strength, bridge expected influence (BEI), bridge

betweenness, and bridge closeness^[36] were used to describe inter-community connections across the four communities defined by the four scales.

The Network Intervention Response Analysis (NIRA) was employed to estimate changes in the network sum score following sequential node threshold perturbations^[24]. In the 0/1-coded Ising model, node thresholds were estimated using IsingFit, representing the baseline log-odds of activation for each node, controlling for the states of other nodes in the network. The mean threshold and the cross-node standard deviation were first calculated from the thresholds of all 55 nodes in the fitted Ising model. Each target node was then perturbed sequentially by decreasing or increasing its original threshold by twice the aforementioned cross-node standard deviation, while keeping the thresholds of other nodes and the original edge weights in the data-generating model unchanged. The same perturbation magnitude was applied to all nodes, rather than using each node's own standard deviation or threshold estimation error. These two scenarios were referred to as the -2SD and +2SD threshold perturbation conditions. For each perturbation scenario, 5,000 observations were simulated, and Ising networks were re-estimated from the simulated data, resulting in three network scenarios: baseline, -2SD perturbation, and +2SD perturbation. The network sum score was defined as the sum of the 55 binary node states for each simulated observation. Node sensitivity under the two simulated perturbation conditions was ranked based on the changes in network sum scores and their 95% confidence intervals following perturbation of each target node.

Welch's t-tests were used to compare network sum scores between the baseline and each node-perturbation scenario, and Bonferroni correction was applied across the 55 node-baseline comparisons within each perturbation direction (- 2SD and +2SD). Subsequently, 5,000 standard bootstrap resamples were performed on the node-baseline differences to estimate the magnitude and uncertainty of node-specific responses. For pairwise node comparisons, the node with the highest point estimate was compared against each of the remaining 54 nodes within each perturbation direction using bootstrap difference tests, with significance determined by Bonferroni-corrected confidence intervals across the 54 comparisons within each direction. The NIRA rankings reflect the theoretical response of the fitted model under pre-specified threshold perturbations and should not be interpreted as observed intervention effects or causal mechanisms.

2.4.4 Network stability and sensitivity analyses

Edge-weight accuracy was assessed with 1,000 nonparametric bootstrap resamples and 95% confidence intervals. Bootstrap difference tests were used to compare edge weights and key centrality indices. Centrality stability was evaluated with 1,000 case-dropping subset bootstraps. The correlation stability coefficient was defined as the largest proportion of cases that could be dropped while the mean correlation with the original estimates remained at least 0.70.

To examine sensitivity to item coding and estimation framework, we also fitted a Gaussian graphical model (GGM) to the original ordinal item scores. We first calculated a polychoric correlation matrix for the 55 items and then estimated a regularized partial-correlation network with graphical LASSO; EBIC

with $\gamma = 0.50$ guided model selection^[37]. The GGM used the same nodes and scale-defined communities as the Ising model. A Pearson correlation-based Mantel test was used to compare the Ising and GGM edge-weight matrices.

2.4.5 General analytical settings

Data management, descriptive analyses, and mediation modeling were conducted using IBM SPSS Statistics 27.0. Ising network estimation, bootstrap analyses, centrality calculation, network visualization, NIRA, GGM sensitivity analysis, and matrix comparison were all performed in R 4.6.1. All statistical tests were two-sided, with the significance level set at $\alpha = 0.05$, and interval estimates are reported with 95% confidence intervals.

2.5 Ethical considerations

The study received approval from the relevant institutional ethics committee and was conducted in accordance with national legislation, institutional requirements, and the Declaration of Helsinki. Written informed consent was obtained from all participants, who were informed that participation was voluntary, their information would remain confidential, and they could withdraw at any time.

3. Results

3.1 Sample characteristics

A total of 1,041 nursing students were included in the analysis. The sample was 90.1% female, 95.4% Han ethnicity, and 63.7% had rural household registration. Most participants were enrolled in bachelor's degree programs (85.6%) and were senior students in their fourth academic year (76.8%). Nursing had been chosen voluntarily by 66.5% of participants and was the first-choice major for 63.5%; 86.0% had begun a clinical internship. Sample characteristics are presented in Table 1.

Table 1
Descriptive statistics of participants.

Variable	Total (N = 1041)
Age, M (Q1, Q3)	22.0 (21.0, 22.0)
Gender, n (%)	
Male	103 (9.9)
Female	938 (90.1)
Ethnicity, n (%)	
Han ethnicity	993 (95.4)
Ethnic minority	48 (4.6)
Household registration, n (%)	
Rural household registration	663 (63.7)
Urban household registration	378 (36.3)
Education level, n (%)	
Junior college	150 (14.4)
Bachelor's degree	891 (85.6)
Academic year, n (%)	
Freshman	50 (4.8)
Sophomore	86 (8.3)
Junior	105 (10.1)
Senior	800 (76.8)
Voluntary choice of nursing major, n (%)	
Yes	692 (66.5)
No	349 (33.5)
Nursing as first-choice major, n (%)	
Yes	661 (63.5)
No	380 (36.5)
Started clinical internship, n (%)	
Yes	895 (86.0)
Note. M, median; Q1, first quartile; Q3, third quartile.	

Variable	Total (N = 1041)
No	146 (14.0)
Note. M, median; Q1, first quartile; Q3, third quartile.	

3.2 Correlation and serial mediation model

Spearman rank correlations among the four scale scores are shown in Supplementary Table 5. Growth mindset was negatively correlated with short-video addiction ($r = -0.327$, $p < 0.01$) and positively correlated with resilience ($r = 0.206$, $p < 0.01$) and general self-efficacy ($r = 0.235$, $p < 0.01$). Resilience and general self-efficacy were positively correlated ($r = 0.328$, $p < 0.01$), and both were negatively correlated with short-video addiction ($r = -0.386$ and -0.334 , respectively; both $p < 0.01$).

The serial mediating roles of resilience and general self-efficacy in the association between growth mindset and short-video addiction were examined using Hayes' PROCESS macro (Model 6); the results are presented in Supplementary Table 6 and Fig. 1. Path analysis showed that growth mindset was positively associated with resilience ($a1: \beta = 0.204$, $p < 0.001$) and general self-efficacy ($a2: \beta = 0.168$, $p < 0.001$), and resilience was positively associated with general self-efficacy ($d: \beta = 0.317$, $p < 0.001$). In the short-video addiction outcome model, resilience ($b1: \beta = -0.291$, $p < 0.001$) and general self-efficacy ($b2: \beta = -0.186$, $p < 0.001$) were both negatively associated with short-video addiction. The total association between growth mindset and short-video addiction was significant ($c: \beta = -0.317$, $p < 0.001$); after both mediators were included, the direct association remained significant ($c': \beta = -0.214$, $p < 0.001$), indicating partial statistical mediation under the prespecified model.

Bootstrap mediation analyses revealed significant direct and indirect effects of growth mindset on short-video addiction (Table 2). The total standardized effect was -0.317 (95% CI $[-0.374, -0.259]$), with a significant direct effect (-0.214 , 95% CI $[-0.269, -0.159]$) and total indirect effect (-0.103 , 95% CI $[-0.130, -0.077]$). Three significant indirect pathways emerged: growth mindset $\rightarrow$ resilience $\rightarrow$ short-video addiction (-0.059 , 95% CI $[-0.080, -0.040]$), growth mindset $\rightarrow$ general self-efficacy $\rightarrow$ short-video addiction (-0.031 , 95% CI $[-0.047, -0.019]$), and growth mindset $\rightarrow$ resilience $\rightarrow$ general self-efficacy $\rightarrow$ short-video addiction (-0.012 , 95% CI $[-0.018, -0.007]$). All CIs excluded zero. Pairwise comparisons of indirect effects confirmed significant differences among the three pathways; the indirect effect via resilience was the strongest, followed by the pathway via general self-efficacy, and the serial pathway through resilience and general self-efficacy exhibited the weakest effect.

Given the cross-sectional measurement of all variables, the identified paths and indirect effects only capture statistical associations under the prespecified model, precluding conclusions regarding temporal sequencing and causal mediation.

Table 2
Bootstrap analysis of the standardized effects between the main variables

Path	Effect	Boot SE	Boot LLCI	Boot ULCI
Total Effect	-0.317	0.029	-0.374	-0.259
Direct effect	-0.214	0.028	-0.269	-0.159
Total indirect effect	-0.103	0.013	-0.130	-0.077
growth mindset → resilience → short-video addiction (Ind1)	-0.059	0.010	-0.080	-0.040
growth mindset → general self-efficacy → short-video addiction (Ind2)	-0.031	0.007	-0.047	-0.019
growth mindset → resilience → general self-efficacy → short-video addiction (Ind3)	-0.012	0.003	-0.018	-0.007
Comparison1:Ind1-Ind2	-0.028	0.013	-0.053	-0.002
Comparison2:Ind1-Ind3	-0.047	0.010	-0.067	-0.030
Comparison3:Ind2-Ind3	-0.019	0.007	-0.034	-0.007
Note. N = 1,041. Effect represents the standardized total, direct, or indirect effect. BootSE represents the standard deviation of the bootstrap sampling distribution of the effect. Boot LLCI and Boot ULCI represent the lower and upper limits of the 95% percentile bootstrap confidence interval, respectively, based on 5,000 bootstrap resamples. An indirect effect was considered statistically significant when its 95% confidence interval did not include zero.				

3.3 Estimated Ising model network

An Ising model was estimated for the 55 dichotomized items from the growth mindset (C1–C6), short-video addiction (D1–D14), resilience (K1–K25), and general self-efficacy (Z1–Z10). The estimated network contained 199 non-zero estimated edges among 1,485 possible edges (density = 13.4%); 171 edges were positive and 28 were negative (Fig. 2a).

3.4 Ising network topology and key node identification

Because the Ising network included both positive and negative edges, traditional strength sums absolute edge weights and therefore cannot reflect the direction of connections. EI retains the signs of edge weights and thus represents a node's net connectivity across the full network, whereas BEI further sums signed connections between a node and nodes in other communities, thereby identifying bridge nodes that connect different constructs.

Accordingly, we calculated expected influence (EI; Fig. 2b) and bridge expected influence (BEI; Fig. 2c) to describe overall signed connectivity and signed connectivity across communities, respectively. K24 (“Persistence despite obstacles”) had the highest EI point estimate (8.394), followed by C2 (7.890) and

C3 (7.139). Bootstrap difference tests did not show significant EI differences between K24 and C2, C3, or Z10 (“Confidence in problem solving”) (Supplementary Fig. 1). K24 should therefore be described as having the highest point estimate, rather than as a uniquely dominant EI node. Z10 had the highest positive BEI (4.193), followed by Z8 (1.685) and K24 (1.156). Bootstrap pairwise tests supported a higher BEI for Z10 than for the other nodes (Supplementary Fig. 2). EI and BEI are signed measures of conditional connectivity and do not establish protective or harmful causal effects.

These findings indicate that although K24 (“Persistence despite obstacles”) had the highest point estimate of overall network connectivity, this advantage was not fully supported by pairwise difference tests. In contrast, Z10 (“Confidence in problem solving”) demonstrated the strongest cross-community connectivity with statistically supported differences. It should be noted that the signed values of EI and BEI reflect the direction and overall magnitude of network associations, and should not be interpreted as evidence of protective or harmful causal effects of the corresponding nodes.

3.5 NIRA simulations of threshold perturbations

Under the -2SD threshold perturbation condition, K13 (“Awareness of support resources”) yielded the lowest network sum score of 17.372, representing a decrease of 1.074 points (5.8%) from the baseline value of 18.447 (Fig. 3a). Under the +2SD threshold perturbation condition, Z10 (“Confidence in problem solving”) yielded the highest network sum score of 19.943, representing an increase of 1.496 points (8.1%) from the baseline (Fig. 3b).

Edge-weight accuracy was assessed separately with nonparametric bootstrap confidence intervals (Supplementary Fig. 3). As shown in Supplementary Table 7, node–baseline comparisons tested whether each simulated perturbation changed the network sum score. After Bonferroni correction for 55 comparisons within each direction, the K13 (“Awareness of support resources”) -2SD and Z10 + 2SD contrasts remained statistically significant (both $p < 0.001$). We then used 5,000 equal-size bootstrap resamples with replacement to quantify uncertainty in the node-specific responses (Supplementary Fig. 4). K13 (“Awareness of support resources”) showed the largest point-estimated decrease under -2SD, with a bootstrap mean decrease of 1.074 and a Bonferroni-adjusted 99.91% CI of [0.739, 1.381]. Z10 showed the largest point-estimated increase under +2SD, with a bootstrap mean increase of 1.495 and a Bonferroni-adjusted 99.91% CI of [1.146, 1.833]. Node-pair bootstrap comparisons did not show that either response was significantly larger than the response of adjacent ranked nodes (Supplementary Table 8).

Thus, K13 (“Awareness of support resources”) and Z10 (“Confidence in problem solving”) had the most extreme point estimates in the two simulated directions, and both showed a stable directional difference from the common baseline. The pairwise comparisons did not establish that either node was superior to the next-ranked nodes. These results identify K13 (“Awareness of support resources”) and Z10 (“Confidence in problem solving”) as nodes for further investigation within the fitted model, not as validated intervention targets.

3.6 Network stability and sensitivity analyses

The Mantel test confirmed significant structural correspondence between the GGM (Supplementary Fig. 5) and Ising networks (Mantel $r = 0.885$, $p < 0.001$).

Case-dropping bootstrap analysis ($B = 1,000$; Supplementary Fig. 6) indicated high stability for edge weights, node strength, and expected influence. Each had a CS-coefficient of 0.75, the maximum value assessable under the default settings of `bootnet::corStability()`. Betweenness had limited stability (CS-coefficient = 0.28), and closeness had low stability (CS-coefficient = 0.21), below the commonly used 0.25 threshold. Interpretations therefore focus on edge weights, strength, and expected influence; betweenness and closeness are reported as supplementary descriptive indices.

4. Discussion

This study combined serial mediation, an item-level Ising network, and NIRA threshold simulations to examine growth mindset and short-video addiction in nursing students. At the construct level, resilience and general self-efficacy were involved in specific and serial indirect associations. At the item level, K24 (“Persistence despite obstacles”) had the highest EI point estimate, Z10 (“Confidence in problem solving”) had the highest BEI, and K13 (“Awareness of support resources”) and Z10 produced the most extreme point-estimated responses in the two NIRA directions.

4.1 Psychological resource pathways linking growth mindset and short-video addiction among nursing students

The mediation results are consistent with earlier studies linking resilience to short-video addiction-related outcomes^[38] and self-efficacy to problematic digital-media use^[20, 21, 39]. They extend this work by examining growth mindset, resilience, and general self-efficacy within one prespecified model in nursing students. The significant indirect associations are compatible with a pattern in which a cognitive belief is related to adaptive psychological resources, which are in turn related to short-video addiction. The data do not establish the temporal order of these variables.

The indirect association through resilience was larger than the association through general self-efficacy, whereas the serial indirect association was smaller. One possible interpretation within the specified total-score model is that resilience items overlap more directly with persistence and behavioral adaptation, while general self-efficacy captures a broader appraisal of capability^[18, 40]. This interpretation concerns the content of the measured constructs and should not be read as evidence that resilience precedes self-efficacy in time.

4.2 Core and bridge nodes in the network

K24 (“Persistence despite obstacles”) had the highest EI point estimate, but its difference from several other high-EI nodes was not statistically supported. The item concerns persistence when obstacles arise. That content is relevant to resilience and overlaps conceptually with perseverance of effort, which has been studied in nursing students^[41, 42]. Its position may therefore reflect the shared connectivity of

persistence-related content across the psychological-resource items. The result is best described as a high point estimate within a group of statistically similar nodes.

Z10 (“Confidence in problem solving”) had the highest positive BEI, and its strongest cross-community connection was with K24. Z10 measures confidence in solving problems, whereas K24 reflects continued effort when problems occur. Their association links an appraisal of capability with a persistence-related response. This may help explain why Z10 connected strongly across scale-defined communities. The result is a statistical feature of the cross-sectional network, not evidence that Z10 transmits an effect to other nodes.

4.3 Node-level sensitivity to NIRA threshold perturbations

NIRA and centrality answer different questions. EI and BEI describe signed connectivity in the estimated network, whereas NIRA evaluates the change in the model-implied network sum score after a node threshold is perturbed^[24, 43]. A node can therefore have a high centrality estimate without producing the largest simulated change, and the reverse can also occur.

K13 (“Awareness of support resources”) produced the largest point-estimated decrease when its threshold was lowered by 2SD. In the fitted Ising model, this perturbation makes activation of the K13 item less likely. K13 concerns awareness of available support resources, not whether support was actually accessed. Studies of nursing and health-professional students have described barriers related to recognizing or locating support services^[44, 45]. This literature provides a context for interpreting the content of K13, but it does not show that changing awareness would change short-video addiction. K13's modest centrality and its NIRA response also illustrate that threshold sensitivity and connectivity are different properties of the fitted model.

Z10 (“Confidence in problem solving”) produced the largest point-estimated increase under the +2SD perturbation and also had the highest BEI point estimate. These results place the item at the intersection of two model summaries: it showed strong signed cross-community connectivity and a large simulated network response. The content of Z10 is a broad judgment about problem-solving capability^[46, 47]. It's association with K24 (“Persistence despite obstacles”) may reflect the relation between perceived capability and persistence when facing difficulty^[46, 48]. Because the node-pair comparisons did not establish that Z10's NIRA response was larger than adjacent ranked responses, its prominence should be treated as a model-based pattern that warrants replication rather than as evidence of a uniquely influential intervention target.

4.4 Research implications

4.4.1 Implications for nursing education and research

At the construct level, the resilience pathway provides a rationale for examining adaptive psychological resources in future nursing research on short-video addiction. At the item level, K24 (“Persistence despite obstacles”), Z10 (“Confidence in problem solving”), and K13 (“Awareness of support resources”)

identify specific contents that can be included in longitudinal or experimental hypotheses. These findings help specify what should be measured next; they do not show that changing any one item would reduce short-video use.

4.4.2 Limitations and future directions

First, the cross-sectional design prevents conclusions about temporal ordering, causal mediation, or reciprocal relationships. Longitudinal studies with repeated measurements are needed to determine how growth mindset, resilience, general self-efficacy, and short-video addiction influence one another over time. Second, all variables were assessed using self-report measures, which may be affected by recall and common-method biases. Future studies could incorporate objective indicators such as application-recorded frequency and duration of short-video use. Third, dichotomization was required for Ising network estimation but reduced the information contained in the original response categories. Sensitivity analyses using alternative thresholds or network models for ordinal data would strengthen future findings. Fourth, NIRA estimates responses to threshold perturbations within a fitted cross-sectional network and does not represent an actual intervention on students' psychological characteristics or behavior. Future applications should also consider permutation tests and repeated-simulation stability analyses recommended for evaluating the robustness of NIRA findings^[42]. Finally, participants were recruited from one Chinese province and were predominantly female. Replication in geographically diverse samples and appropriately powered subgroup comparisons are required before the findings can be generalized to broader nursing student populations.

5. Conclusion

This study examined associations among growth mindset, resilience, general self-efficacy, and short-video addiction in nursing students using serial mediation, an item-level Ising network, and NIRA threshold simulations. Growth mindset was associated with short-video addiction both directly and through specific and serial indirect pathways. K24 ("Persistence despite obstacles") had the highest EI point estimate, Z10 ("Confidence in problem solving") had the highest positive BEI, and K13 ("Awareness of support resources") and Z10 showed the most extreme point-estimated NIRA responses in the two perturbation directions. The findings describe relationships and model-based responses in this sample. They do not establish temporal or causal mechanisms, nor do they validate intervention targets.

Abbreviations

CD-RISC

Conner-Davidson Resilience Scale

GMS

Growth Mindset Scale

GSES

General Self-Efficacy Scale

SVAS
Short Video Addiction Scale
EI
Expected Influence
BEI
Bridge Expected Influence
NIRA
NodeIdentifyR Algorithm

Declarations

Ethics approval and consent to participate

This study was approved by the Ethics Review Committee of the Hospital of Integrated Traditional Chinese and Western Medicine, Southern Medical University (approval No. 202606-K4; date: July 2, 2026). Written informed consent was obtained from all participants, who were assured that their information would remain confidential. Participants were allowed to withdraw from the study at any time. The study was conducted in accordance with national legislation, institutional requirements, and the principles of the Declaration of Helsinki.

Clinical trial number

not applicable.

Consent for publication

Not applicable

Availability of data and materials

The data that support this study are available from the first author upon reasonable request.

Competing interest

The authors have no conflicts of interest to disclose.

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Authors' contributions

H.L.J.: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Y.D.W.:** Writing – review & editing, Software, Methodology, Investigation, Conceptualization. **J.J.X.:** Writing – review & editing, Methodology, Software, Investigation. **J.H.W.:** Writing – review & editing, Methodology, Software. **Y.X.:** Writing – original draft, Investigation. **M.D.W.:** Writing – review & editing. **W.H.Z.:** Software, Investigation. **J.Z.:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

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Figures

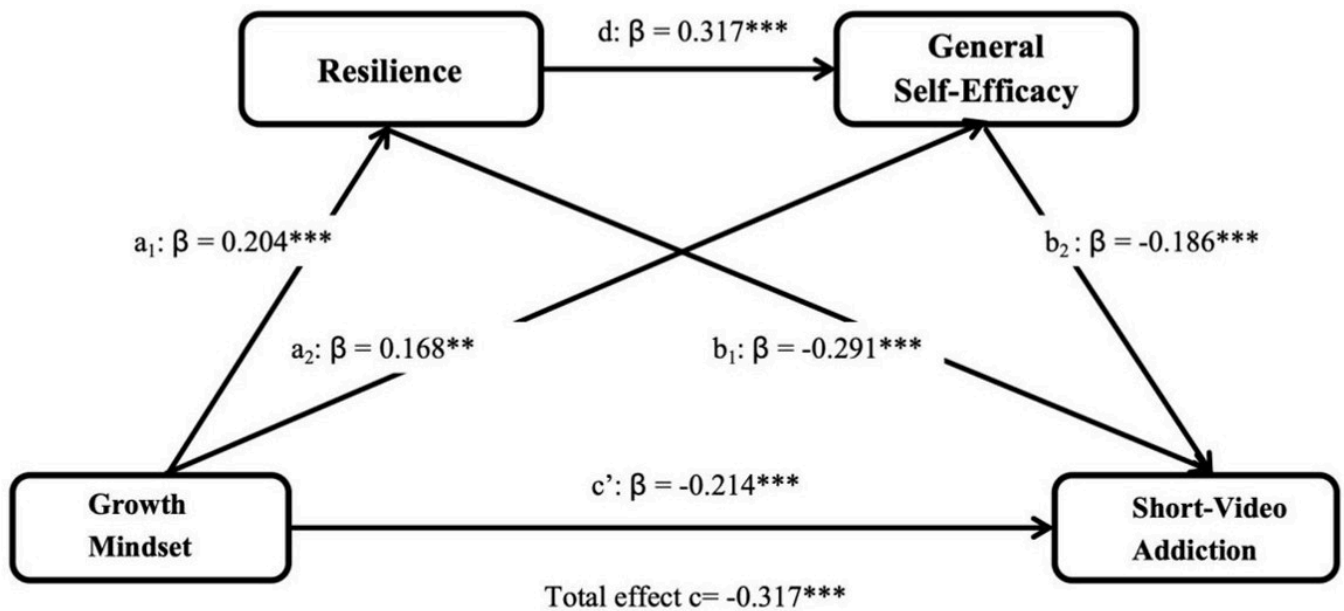


Figure 1

Covariate-adjusted serial mediation model of the association between growth mindset and short-video addiction through resilience and general self-efficacy.

Note. All four constructs were entered as observed total scores. Values on arrows are standardized regression coefficients; c denotes the total association, and c' denotes the direct association after both mediators were included. $^{***}p < 0.001$.

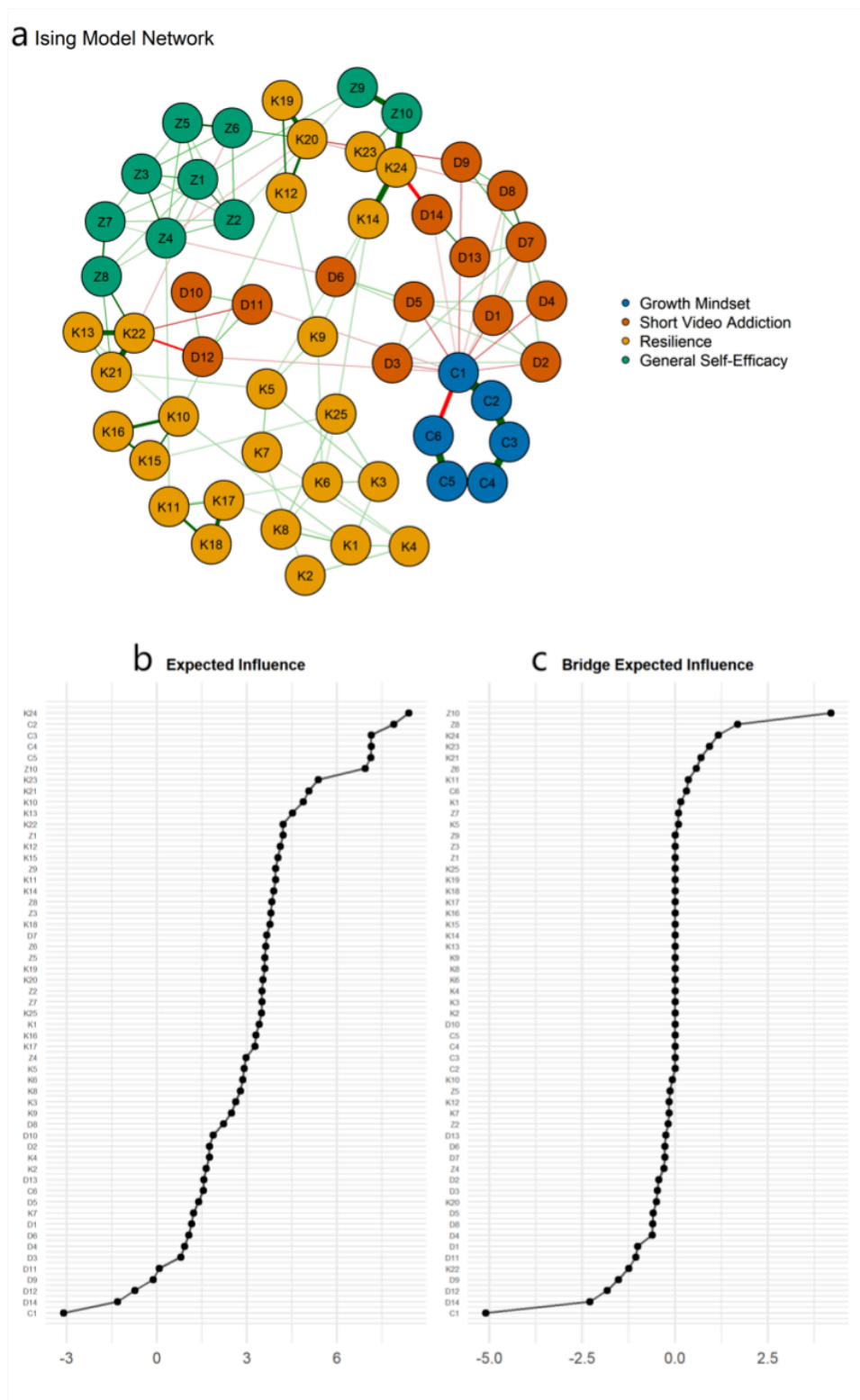


Figure 2

Visualized Ising network based on the 55 study items

Note. (a) Estimated Ising network. Edges represent conditional associations (green = positive, red = negative); edge thickness reflects association magnitude. (b) Expected influence (EI) for each node, sorted in ascending order. (c) Bridge expected influence (BEI) for each node, sorted in ascending order.

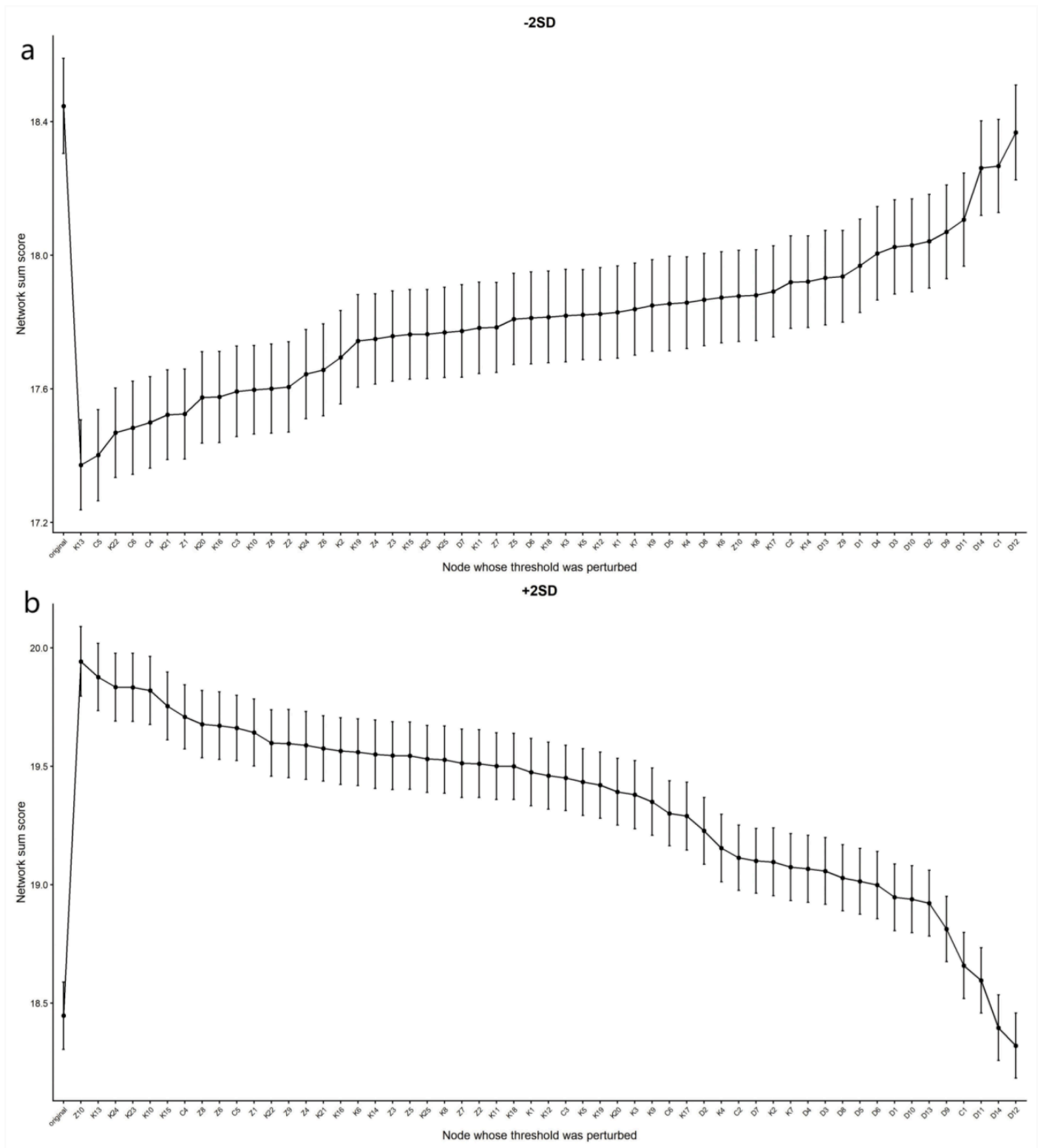


Figure 3

NIRA-based threshold-perturbation simulations.

Note. (a) Change in the expected network sum score when node thresholds were decreased by 2 standard deviations ($-2SD$), corresponding to the $-2SD$ threshold-perturbation scenario. (b) Change in the expected network sum score when node thresholds were increased by 2 standard deviations ($+2SD$),

corresponding to the +2SD threshold-perturbation scenario. The x-axis lists individual nodes ordered according to the network sum score following perturbation of each node's threshold. Vertical error bars indicate the bootstrapped 95% confidence intervals (CIs) for the network sum score under each node-specific perturbation.

Supplementary Files

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