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The influence of negative life events on psychological resilience and theory of mind in adolescents: evidence from Gaussian graphical modeling and Bayesian network analysis

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Abstract

Background

Adolescence is a critical period for coping with life stress and developing adaptive capacities. However, the interrelations among negative life events, psychological resilience, and theory of mind have rarely been characterized at the component level, and the direction of their associations remains unclear. The present study aimed to map the associations, central nodes, and probable directional dependencies among these three systems in adolescents.

Methods

A total of 1,191 adolescents (525 boys and 666 girls; aged 13–18 years, mean = 15.50, SD = 1.15) were recruited from 40 secondary vocational schools in Guangdong Province, China. Negative life events, psychological resilience, and theory of mind were assessed with the Adolescent Self-Rating Life Events Checklist, the Connor-Davidson Resilience Scale, and a comic-strip theory-of-mind task, respectively. Controlling for sex, age, and family socioeconomic status, we combined Gaussian graphical modeling with Bayesian network analysis to estimate the association structure, node centrality, and probable directional dependencies.

Results

The Gaussian graphical model revealed predominantly negative connections between negative life events and both resilience and theory of mind. The punishment factor showed the highest expected influence in the network, and the strength facet of resilience showed the highest bridge expected influence. The Bayesian network further indicated a bidirectional, domain-asymmetric pattern of directional dependence between stress and resilience: the “other” factor of negative life events pointed to the strength facet, whereas tenacity pointed to the interpersonal-relationship factor. Theory of mind showed no stable directional links with negative life events or resilience.

Conclusions

In adolescents, negative life events and psychological resilience constitute a dynamically interacting, directionally asymmetric adaptive system, whereas theory of mind—as a relatively stable social-cognitive capacity—appears to operate largely independently of this system. These findings provide component-level and directional evidence on stress–adaptation mechanisms in adolescents and suggest that interventions targeting punishment experiences and the strength facet of resilience may yield broader systemic benefits.

Background

Adolescence is a developmental stage of rapid physical and psychological change and abrupt shifts in social roles, and it is also a period of heightened sensitivity to environmental stress [1]. During this stage, academic streaming, the reconfiguration of interpersonal relationships, and the exploration of self-identity expose adolescents to a wide range of negative life events, the accumulation of which often has profound effects on their mental health and long-term adaptive trajectories [2]. In China, adolescents in secondary vocational schools frequently face multiple pressures, including academic evaluation, social comparison, and disparities in educational resources, and constitute a relatively understudied yet potentially high-risk population. A deeper understanding of how negative life events interact with individuals' adaptive resources and social-cognitive abilities is therefore important both for elucidating the mechanisms of adolescent psychological adaptation and for informing precision interventions in school mental health.

Negative life events refer to events experienced over a given period that exert an adverse psychological impact, and they have a markedly multidimensional structure. As operationalized in the Adolescent Self-Rating Life Events Checklist (ASLEC), for example, negative life events can be further divided into several domains, including interpersonal relationships, academic stress, punishment, loss, health and adaptation, and other events [3]. Research has shown that the accumulation of negative life events is an important risk factor for adolescent depression and emotional problems, and that the type and timing of events jointly shape their psychological consequences [4]. Notably, stressors in different domains may act on the adaptive system through different mechanisms; however, prior work has largely treated negative life events as a single whole and has paid little attention to the differential roles of their constituent domains in interacting with adaptive resources.

In the face of stress, individuals do not respond passively but adapt actively through psychological resilience. Resilience refers to the dynamic process of maintaining good adaptation in the face of adversity, trauma, or major stress [5]. From a developmental psychopathology perspective, resilience is not a fixed personality trait but an adaptive outcome that emerges from the dynamic interplay of risk and protective factors over the course of development [6, 7]. Connor and Davidson [8] further distinguished components of resilience such as tenacity, strength, and optimism. Studies have generally found a negative association between negative life events and resilience [4], yet the direction of this relationship has long been debated: does stress erode resilience, or are more resilient individuals themselves less exposed to stress or inclined to appraise stressors as less threatening [9]? Cross-sectional designs and latent-variable approaches have made this direction difficult to disentangle.

Beyond adaptive resources, social-cognitive ability is also a key foundation for adolescents' coping with social stress. Theory of mind (ToM) refers to the ability to infer the mental states—such as intentions, beliefs, and emotions—of oneself and others [10]. Research has further distinguished cognitive ToM (inferring others' intentions and beliefs) from affective ToM (inferring others' emotional states), which rely on partially dissociable processing mechanisms [11]. Social-cognitive ability continues to develop

during adolescence, and sensitivity to interpersonal cues increases markedly [1, 12]. In principle, good ToM helps individuals accurately interpret interpersonal cues and effectively mobilize social support, thereby buffering the impact of interpersonal stress; conversely, sustained stress and adversity may impair social-cognitive processing, and such effects are often domain-specific [13]. However, empirical evidence on the relations of ToM to life stress and resilience remains limited and inconsistent, and the mutual positioning of these three constructs is largely unknown.

In sum, although research on negative life events, psychological resilience, and ToM is relatively abundant, three gaps remain. First, the three constructs have largely been treated as single reflective latent variables, and research has stopped at "whole-to-whole" associations, making it difficult to reveal component-level information—such as which type of stressor is most critical and which resilience facet bears the brunt of stress. Second, the three constructs have rarely been examined within a single system, so their mutual positioning and the cross-domain channels connecting them remain unclear. Third, constrained by cross-sectional designs, the direction of influence between stress and adaptation is difficult to infer. Overcoming these limitations requires an analytic framework that can characterize system structure at the component level while also permitting directional inference.

The recently developed network-analysis approach offers a new opportunity in this regard. In contrast to reflective models that treat constructs as latent common causes of their indicators, the network perspective conceptualizes psychological phenomena as systems that emerge from direct, mutually reinforcing interactions among components [14–16]. Within this framework, the Gaussian graphical model (GGM) estimates the partial correlation between each pair of components after controlling for all other variables; expected influence (EI) quantifies a node's overall influence within the network; and bridge expected influence (BEI) identifies the "bridge" nodes that connect different domains [17–19]. However, the GGM characterizes undirected associations and cannot indicate the direction of influence. Bayesian network analysis, by contrast, is based on a directed acyclic graph (DAG) and can perform probabilistic directional inference of dependency relations from cross-sectional data [20, 21], thereby providing clues for generating causal hypotheses. Combining the two—describing the topology and strength of the system while probing the probable direction of influence—is well suited to characterizing the complex relations among negative life events, resilience, and ToM in adolescents. It should be noted that a Bayesian DAG based on cross-sectional data suggests, rather than proves, causal relations, and its results should be interpreted as directional hypotheses awaiting further testing.

On this basis, focusing on adolescents in Chinese secondary vocational schools and controlling for sex, age, and family socioeconomic status, the present study combined the GGM with Bayesian network analysis to systematically characterize the association structure, central nodes, and probable directional dependencies among negative life events, resilience, and ToM. Specifically, we proposed the following hypotheses and research question: (1) the components of negative life events are negatively associated with the components of resilience (H1); (2) which components of negative life events show the highest centrality, and which resilience facet serves as the cross-domain bridge (RQ1); (3) the Bayesian network will reveal a predominantly "negative life events → resilience" direction and may show a reverse

“resilience → stress” path in the interpersonal domain (H2); and (4) given the developmental consolidation of ToM by mid-adolescence, ToM will be relatively decoupled from the stress–resilience system (H3).

Methods

Participants

Using convenience sampling, adolescents from 40 secondary vocational schools in Guangdong Province, China, were recruited as participants, with data collected in March 2026. The final valid sample comprised 1,191 adolescents (525 boys and 666 girls), aged 13–18 years, with a mean age of 15.50 years (SD = 1.15). Because current network-analytic methods cannot accommodate computations involving missing values [18], individual missing values were imputed using the mice package in R [22] to ensure analytic accuracy and sample completeness. The study was approved by the Ethics Committee of Guangdong Polytechnic Normal University (approval no. 20250801). Written informed consent was obtained from the parents, head teachers, and students, and all participants were in good physical, intellectual, auditory, and visual health.

Measures

Adolescent Self-Rating Life Events Checklist. Negative life events over the preceding 12 months and their psychological impact were assessed with the ASLEC developed by Liu et al. [3]. The scale comprises 27 items grouped into six factors: interpersonal relationship (items 1, 2, 4, 15, 25), academic stress (items 3, 9, 16, 18, 22), punishment (items 17, 19, 20, 21, 23, 24), loss (items 12, 13, 14), health and adaptation (items 5, 8, 11, 27), and other (items 6, 7). For each event, respondents first indicated whether it had occurred; if it had, they rated its psychological impact on a 6-point scale (0 = did not occur to 5 = extremely severe impact), with higher scores indicating greater psychological impact. In the present sample, Cronbach’s α was 0.921 for the total scale and ranged from 0.880 to 0.950 for the subscales, indicating that the ASLEC is suitable for assessing negative life events among Chinese adolescents.

Connor-Davidson Resilience Scale. Psychological resilience was assessed with the Connor-Davidson Resilience Scale (CD-RISC) developed by Connor and Davidson [8]. The 25-item scale comprises three subscales: tenacity (13 items: 1, 2, 4, 5, 7, 8, 10, 11, 13, 14, 16, 17, 19), strength (8 items: 3, 6, 9, 12, 15, 18, 20, 22), and optimism (4 items: 21, 23, 24, 25). Items are rated on a 5-point Likert scale (0 = not true at all to 4 = true nearly all the time), with no reverse-scored items; higher scores indicate greater resilience. In the present sample, Cronbach’s α was 0.834 for the total scale and ranged from 0.810 to 0.868 for the subscales, indicating that the scale is suitable for assessing resilience among Chinese adolescents.

Theory of Mind task. ToM was measured with a comic-strip paradigm adapted from Völlm et al. [23]. The materials comprised 40 comic strips organized into eight blocks of five strips each, with the within-block presentation order randomized and counterbalanced to control for order effects. Four conditions were administered: cognitive ToM (cToM), affective ToM (aToM), single-character physical causality (Physical 1), and two-character physical causality (Physical 2). The cToM condition presented a single-character scenario without social interaction or emotional cues and required participants to infer the character's behavioral intention; the aToM condition presented a two-character interactive scenario with social and emotional information and required participants to judge the character's emotional state; Physical 1 and Physical 2 were control conditions involving single- and two-character physical-causal reasoning, matched to cToM and aToM respectively to rule out the contribution of basic physical cognition and logical reasoning to ToM processing. Each condition comprised 10 valid trials, for 40 trials in total.

Each block followed a standardized procedure: a 6-s guiding question first initiated the relevant processing mode ("What will the protagonist do next?" for cToM; "What would make the protagonist feel better?" for aToM; and "What is most likely to happen next?" for both physical-causality conditions); a 6-s context strip then presented the full story background; finally, two strips representing alternative endings were presented at the bottom of the screen for 4.5 s, and participants were required to select the logically appropriate ending by key press within the time limit. Accuracy was computed for each condition. To isolate ToM ability from basic physical cognition, core ToM accuracy was corrected by the corresponding control task: cognitive ToM = cToM accuracy − Physical 1 accuracy; affective ToM = aToM accuracy − Physical 2 accuracy. In the present sample, Cronbach's α for the ToM task was 0.744, indicating that the task is suitable for assessing ToM among Chinese adolescents.

Data analysis

Descriptive statistics were computed in SPSS 31.0, and Gaussian graphical modeling and Bayesian network analysis were conducted in R 4.5.3. Network analysis followed the standardized guidelines of Epskamp et al. [17], encompassing estimation, visualization, centrality assessment, and accuracy/stability testing.

Network analysis based on the Gaussian graphical model. *(1) Network estimation.* A regularized partial-correlation network among the dimensions of negative life events, resilience, and ToM was estimated using the qgraph package in R (version 4.5.3). After controlling for sex, age, and family socioeconomic status as covariates, a Gaussian graphical model (GGM) was used to estimate pairwise relations [17]. The least absolute shrinkage and selection operator (LASSO) was then applied to remove non-significant edges and improve model accuracy [18]; combining the GGM with LASSO captures key relations while avoiding spurious associations, a strategy particularly suited to large-scale or high-dimensional data and yielding robust, interpretable network structures [24]. The network was visualized using the Fruchterman-Reingold algorithm, with nodes grouped into three communities (negative life events, resilience, and ToM) and thicker edges denoting stronger associations. *(2) Centrality and bridge centrality.* Expected

influence (EI) was used to quantify a node's influence within the network, and bridge expected influence (BEI) was used to quantify a node's influence on the nodes of the other communities [17–19]. *(3) Accuracy and stability checks.* Using the bootnet package, edge-weight accuracy was assessed via 95% confidence intervals from non-parametric bootstrapping (n = 1,000); the stability of node and bridge centrality was examined via case-dropping bootstrapping (n = 1,000) and quantified with the correlation-stability (CS) coefficient (CS > 0.25 acceptable; CS > 0.50 good); and between-node differences in edge weights, centrality, and bridge centrality were examined with bootstrapped difference tests (n = 1,000, α = 0.05).

Bayesian network analysis. After controlling for sex, age, and family socioeconomic status, a Bayesian network was used to model the dependency relations among variables. A directed acyclic graph (DAG) was learned with the hill-climbing algorithm in the bnlearn package and iteratively optimized according to the Bayesian information criterion (BIC) [20, 21]. To ensure structural stability, the network was estimated with 10,000 bootstrap resamples [25], and high-frequency edges were selected using the optimal cut-point method [26]; a direction from X to Y was retained in the final DAG only if it appeared in at least 51% of the bootstrapped networks. For visualization, both a directional-probability graph (edge thickness reflecting the probability of a given direction across the bootstrapped networks) and a structural-contribution graph (edge thickness reflecting the edge's contribution to overall model fit, indexed by its effect on the BIC) were presented.

Results

Descriptive statistics

Descriptive statistics indicated that item scores were approximately normally distributed and suitable for network analysis (Table 1).

Table 1
Descriptive statistics for the dimensions of negative life events, psychological resilience, and theory of mind

Variable	Label	M	SD	Skewness	Kurtosis
Negative life events					
Interpersonal relationship	A1	6.12	4.71	0.51	−0.37
Academic stress	A2	5.51	4.06	0.58	−0.24
Punishment	A3	3.95	4.92	1.52	1.90
Loss	A4	2.17	2.97	1.61	2.16
Health and adaptation	A5	3.53	3.13	0.90	0.40
Other	A6	3.29	3.24	1.22	1.42
Psychological resilience					
Tenacity	D1	38.27	9.71	0.23	1.03
Strength	D2	24.18	5.73	0.23	1.21
Optimism	D3	11.60	2.87	0.25	1.40
Theory of mind					
Cognitive theory of mind	I1	0.13	0.25	0.02	0.23
Affective theory of mind	I2	0.05	0.22	0.38	1.45

Gaussian graphical model of negative life events, resilience, and theory of mind

Network estimation. As shown in Fig. 1, the estimated regularized GGM comprised 11 nodes and 30 non-zero edges, including 12 non-zero cross-community edges (2 positive and 10 negative). Among the cross-community edges, the strongest negative bridge connections were health and adaptation–strength, other–strength, and academic stress–affective ToM (all edge weights = − 0.03). In addition, interpersonal relationship–tenacity and punishment–strength showed relatively strong negative bridge connections (both edge weights = − 0.02). These results indicate that negative life events were negatively associated, to varying degrees, with both resilience and ToM (detailed edge weights are provided in Additional file 1: Table S1).

Centrality and bridge centrality. As shown in Fig. 2, the node with the highest centrality was punishment (EI = 1.09), indicating the strongest expected influence on the network. The node with the highest bridge centrality was strength (BEI = − 0.08), indicating the strongest negative bridge expected influence on the other two communities.

Accuracy and stability. After 1,000 non-parametric bootstraps, the CS coefficients for EI and BEI were 0.75 and 0.28, respectively, indicating good stability (Additional file 1: Fig. S1). The 95% confidence intervals around edge weights were small to moderate (Additional file 1: Fig. S2), indicating good accuracy. Difference tests for centrality, bridge centrality, and edge weights are shown in Additional file 1: Figs. S3–S5.

Bayesian network of negative life events, resilience, and theory of mind

After 10,000 bootstrap resamples, edges were selected using the optimal cut-point method proposed by Scutari and Nagarajan [26], retaining those that recurred in at least 51% of the samples (see Fig. 3). The directedness and acyclicity of the DAG permit inference about causal relations among variables and identify the model that best fits these relations.

In the directional-probability DAG (Fig. 3a), the thickest cross-community edge was other → strength (directional probability = 0.81; i.e., the same direction appeared in 8,100 of the 10,000 bootstrapped networks), indicating that the other factor of negative life events was the parent of strength and could substantially predict the probability of strength; given their negative GGM association, this was inferred to be a negative directional path. In addition, tenacity → interpersonal relationship formed a relatively thick cross-community edge (directional probability = 0.70; i.e., 7,000 of the 10,000 bootstrapped networks), likewise inferred to be negative. These results suggest a negative, bidirectional interaction between negative life events and resilience, via other → strength and tenacity → interpersonal relationship. Unexpectedly, no directional links were found between ToM and either negative life events or resilience, indicating that ToM may not have a causal relationship with negative life events or resilience.

In the structural-contribution DAG (Fig. 3b), the three thickest edges were punishment → other, tenacity → optimism, and punishment → loss (BIC = − 616.27, − 542.87, and − 412.34, respectively), indicating that these three directed edges contributed most strongly to the overall Bayesian network model. On this basis, negative life events contributed most to the DAG and were most likely to exert directional influence on resilience. Furthermore, ToM produced no change in BIC in relation to negative life events or resilience, further confirming the absence of a causal relationship between them. Directional probabilities and BIC values for all edges are provided in Table 2.

Table 2
Directional probabilities and BIC values determining edge thickness in the DAG

From	To	Directional probability	BIC
A2	A1	0.72	−158.61
A3	A2	0.68	−52.91
A3	A4	0.63	−412.34
A3	A5	0.67	−21.53
A3	A6	0.57	−616.27
A4	A2	0.53	−1.21
A4	A5	0.63	−30.50
A5	A1	0.71	−26.49
A5	A2	0.58	−102.85
A6	A1	0.67	−29.24
A6	A5	0.64	−87.99
A6	D2	0.81	−5.65
D1	A1	0.70	−5.77
D1	D2	0.63	−393.13
D1	D3	0.60	−542.87
D3	D2	0.53	−113.80

Note. A1–A6 = negative life events factors; D1–D3 = resilience facets (see Table 1 for full labels). The directional probability is the proportion of bootstrapped networks in which the edge took the indicated direction; BIC denotes the edge's contribution to overall model fit (a larger absolute value indicates a greater contribution).

Discussion

Combining Gaussian graphical modeling with Bayesian network analysis and controlling for sex, age, and family socioeconomic status, the present study systematically characterized the association structure, central nodes, and probable directional dependencies among negative life events, resilience, and ToM in adolescents. Negative life events were generally negatively connected with both resilience and ToM; punishment was the central node of the network and strength was the key bridge connecting the domains; stress and resilience showed a bidirectional, asymmetric pattern of directional dependence; and ToM was relatively decoupled, in directional terms, from the stress–resilience system. These findings are discussed in turn within the theoretical framework below.

Network structure of negative life events, resilience, and theory of mind

The GGM showed that 10 of the 12 cross-community edges were negative, indicating a generally antagonistic relationship between negative life events and both resilience and ToM. The strongest negative bridge connections were health and adaptation–strength, other–strength, and academic stress–affective ToM (all edge weights = − 0.03). This pattern is consistent with the conservation of resources perspective: the cumulative impact of life stress continually depletes an individual's limited adaptive resources, thereby weakening resilience [27]. Notably, negative bridges converged most densely on strength, suggesting that this resilience facet—centered on mastery and self-efficacy—may be the first to erode under multiple stressors.

Centrality analysis showed that punishment had the highest expected influence (EI = 1.09), exerting the strongest overall influence on the network. This finding carries developmental and cultural significance. In Chinese educational settings—particularly secondary vocational schools—experiences of punishment are often closely tied to shame, frustrated autonomy, and social-evaluative threat, and may therefore be especially psychologically pervasive, readily spreading to other stress and adaptive components. From a network perspective, central nodes are leverage points at which intervention can yield the greatest systemic benefit [14], suggesting that targeting punishment experiences may be more efficient than addressing all stressors uniformly.

For bridge centrality, strength showed the highest bridge expected influence (BEI = − 0.08), supporting its role as a conduit through which stress enters the resilience system. However, this should be interpreted with caution: although the CS coefficient for bridge expected influence (0.28) met the acceptable threshold, it was substantially lower than that for expected influence (0.75). Thus, conclusions regarding central nodes are robust, whereas conclusions regarding bridge nodes are less stable and require replication in independent samples. Accordingly, our interpretation of the bridging role of strength should be regarded as preliminary.

Bidirectional, domain-asymmetric directional dependence between stress and resilience

Relative to the undirected associations revealed by the GGM, the Bayesian network further characterized probable directions among the variables—our most theoretically informative finding. In the directional-probability graph, the thickest cross-community edge was other → strength (directional probability = 0.81), indicating that the other factor of negative life events was the parent of strength; combined with their negative GGM association, this represents a negative path from stress to resilience. This direction is consistent with resource-depletion/stress-sensitization mechanisms, whereby diffuse negative events weaken strength by continually depleting adaptive resources [9, 27].

However, not all stress–resilience relations followed the same direction. Tenacity → interpersonal relationship also formed a relatively thick cross-community edge (directional probability = 0.70), with the tenacity facet of resilience pointing back to the interpersonal-relationship factor of negative life events. This reverse path can be explained by stress generation theory: individuals' own characteristics shape their exposure to, and appraisal of, life events—especially interpersonal, dependent events [28]. More tenacious individuals may handle interpersonal situations more constructively, thereby generating fewer interpersonal stressors or appraising existing ones as less impactful.

Taken together, our findings reveal a previously underdescribed picture: the direction of stress–resilience influence is domain-asymmetric. In the interpersonal domain, resilience (tenacity) points back to stress, consistent with stress generation; whereas in other stress domains, stress points to resilience, consistent with resource depletion. This bidirectional loop is precisely what the transactional model of developmental psychopathology predicts: individuals and their environments shape each other over the course of development, with risk and protective processes dynamically intertwined [6, 29]. The structural-contribution graph further showed that negative life events contributed most to the DAG (e.g., punishment → other and punishment → loss had the largest BIC changes, − 616.27 and − 412.34), indicating that, among the three systems, negative life events were most likely to play a causal "driving" role. This finding has important intervention implications: building resilience may not only enhance adaptation but also proactively reduce exposure to interpersonal stress, supporting a proactive, resource-building approach to intervention.

Directional decoupling of theory of mind from the stress–resilience system

A surprising but theoretically meaningful finding was that ToM showed no stable directional links with either negative life events or resilience and produced no change in BIC in the structural-contribution graph. This "decoupling" can be understood at both theoretical and methodological levels.

Theoretically, at least two complementary explanations are plausible. The first is developmental consolidation: participants' mean age was 15.50 years, placing them in mid-adolescence, by which point the basic computational machinery of ToM has largely matured and crystallized and may therefore be relatively insensitive to life stress experienced over the preceding 12 months [1, 30]. The second is a difference in functional level: ToM is a relatively stable social-cognitive capacity, whereas the impact of negative events and resilience are more state-like and fluctuating, operating on a different functional layer and timescale, so that their coupling is naturally weak. Notably, large-sample adult research has shown that childhood adversity is associated mainly with specific social-cognitive domains such as ToM but has limited effects on others (e.g., face processing), indicating that adversity–social-cognition associations are markedly domain-specific [13]. In the present study, cross-community edges involving ToM were very sparse, the most notable being only a weak, undirected negative connection between academic stress and affective ToM (edge weight = − 0.03), consistent with a picture of weak, non-

directional coupling. Overall, as a relatively crystallized social-cognitive capacity, ToM may operate largely independently of the affective–motivational stress–resilience system.

Methodologically, this decoupling also warrants caution. First, negative life events and resilience were both self-reported, whereas ToM was assessed via objective behavioral performance (accuracy); cross-method associations are typically weaker than within-method associations. The “decoupling” of ToM may therefore partly reflect method separation, while the close stress–resilience connection may be partly inflated by common method variance [31]. Second, the ToM indices were control-corrected difference scores with very low means (cognitive ToM, M = 0.13; affective ToM, M = 0.05) and modest reliability (α = 0.744), introducing floor effects and restricted variance that systematically attenuate associations with other variables. A prudent conclusion is therefore that ToM is relatively decoupled from the stress–resilience system; whether this reflects genuine functional autonomy or measurement constraints awaits clarification in multimethod, longitudinal research.

Theoretical and practical implications

Theoretically, this study makes three contributions. First, it characterized the mutual positioning of the three systems—negative life events, resilience, and ToM—at the component level, moving beyond the “whole-to-whole” latent-variable approach to reveal finer-grained information, such as which stressor is most critical (punishment) and which resilience facet receives stress (strength). Second, by combining the GGM with Bayesian networks, it offers a methodological template for moving from undirected associations to directional hypotheses: the former characterizes the structure and strength of the system, whereas the latter probes the probable directions of influence. Third, the data tested and largely confirmed an overall prediction derived from developmental psychopathology, the transactional model, and social-cognitive developmental theory—namely, a predominantly negative, directionally asymmetric stress–resilience subsystem alongside a ToM subsystem that is weakly correlated and causally decoupled.

Practically, this study identifies several intervention targets for adolescents, especially those in vocational settings. First, as the central node of the network, punishment should be a priority target for school-based stress interventions; targeting central nodes may produce broader systemic benefits through network cascade effects. Second, given the reverse path from tenacity to interpersonal relationship, proactive resilience-building—particularly cultivating tenacity—may carry the added benefit of reducing exposure to interpersonal stress, suggesting that intervention should focus not only on post-hoc buffering but also on the upfront building of resources. Finally, because ToM is relatively independent of the stress–resilience system, interventions targeting stress and resilience may not concurrently improve social cognition, and the two may require relatively separate intervention pathways.

Limitations and future directions

This study has several limitations. First, it was cross-sectional; the causal directions suggested by the Bayesian DAG are hypothesis-generating and cannot be equated with true causal relations. Future work should test directionality more rigorously using longitudinal designs such as panel networks or cross-

lagged panel networks. Second, negative life events and resilience were both self-reported, raising the possibility of common method variance and social desirability bias, whereas ToM was assessed with difference scores subject to floor effects and restricted variance, which may underestimate its true associations; multimethod, ecologically valid measures are therefore warranted. Third, convenience sampling from secondary vocational schools in a single province limits generalizability, although it also makes the conclusions more pertinent to this specific high-risk population. Fourth, only sex, age, and family socioeconomic status were controlled, leaving potential confounders such as prior mental health history and parenting style unmeasured. Fifth, the stability of bridge centrality was only acceptable, so the related conclusions require replication in independent samples. Moreover, the central role of punishment may be culturally and contextually specific, and its generalizability awaits cross-cultural testing.

Future research could proceed in several directions: using longitudinal designs to formally test the causal direction between stress and resilience; conducting experimental or intervention studies targeting central nodes to test the “central-node-as-leverage-point” hypothesis; adopting multimethod, behaviorally ecological measures of ToM to improve its variance; conducting cross-cultural comparisons to delineate the boundaries of the central role of punishment; and incorporating neural and physiological indices to build multilevel psychological networks.

Conclusions

In adolescents, negative life events and psychological resilience constitute a dynamically interacting, directionally asymmetric adaptive system: diffuse stress depletes resilience, while resilience in turn suppresses interpersonal stress, with punishment serving as the central node of the system and strength as a key cross-domain bridge. Meanwhile, ToM, as a relatively crystallized social-cognitive capacity, may operate largely independently of this system. These findings deepen our understanding of stress–adaptation mechanisms in adolescents at both the component and directional levels and provide empirical support for precision interventions that target central nodes.

Abbreviations

ASLEC
Adolescent Self-Rating Life Events Checklist
CD-RISC
Connor-Davidson Resilience Scale
ToM
theory of mind
cToM
cognitive theory of mind
aToM
affective theory of mind

GGM
Gaussian graphical model
LASSO
least absolute shrinkage and selection operator
DAG
directed acyclic graph
BIC
Bayesian information criterion
EI
expected influence
BEI
bridge expected influence
CS
correlation stability
SES
socioeconomic status
SD
standard deviation.

Declarations

Ethics approval and consent to participate. This study was approved by the Ethics Committee of Guangdong Polytechnic Normal University (approval no. 20250801) and was conducted in accordance with the Declaration of Helsinki. Written informed consent was obtained from all participating students and from their parents or legal guardians, as well as from the head teachers.

Consent for publication. Not applicable.

Availability of data and materials. The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request. *(If you deposit the data and analysis code in a public repository such as the Open Science Framework, provide the persistent link/DOI here.)*

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Authors' contributions. *(Example: [A.A.] and [B.B.] designed the study; [C.C.] collected the data; [A.A.] analysed the data and drafted the manuscript; [B.B.] and [D.D.] revised the manuscript critically for important intellectual content. All authors read and approved the final manuscript.)*

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Use of large language models. *(Per BMC policy, disclose any LLM assistance, e.g.: "The authors used a large language model to assist with translation and language editing of an earlier Chinese draft. All content was subsequently reviewed, verified, and approved by the authors, who take full responsibility for the work." Edit or remove as appropriate.)*

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Figures

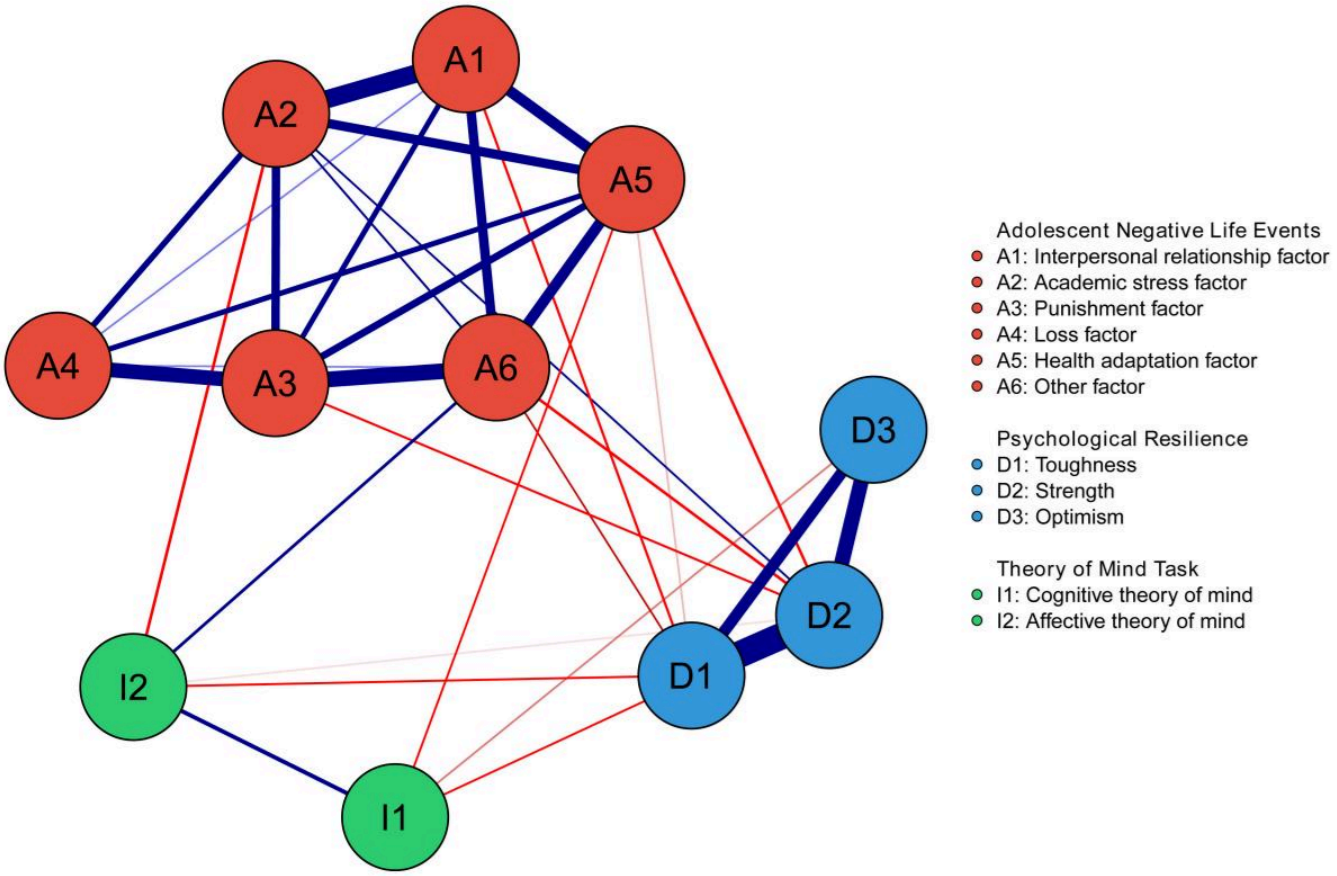


Figure 1

GGM network structure among negative life events, psychological resilience, and dimensions of theory of mind. ***Note.*** Edges represent horizontal connections between variables, with blue edges indicating positive associations and red edges indicating negative associations. The thicker the edge and the more saturated the color, the stronger the association.

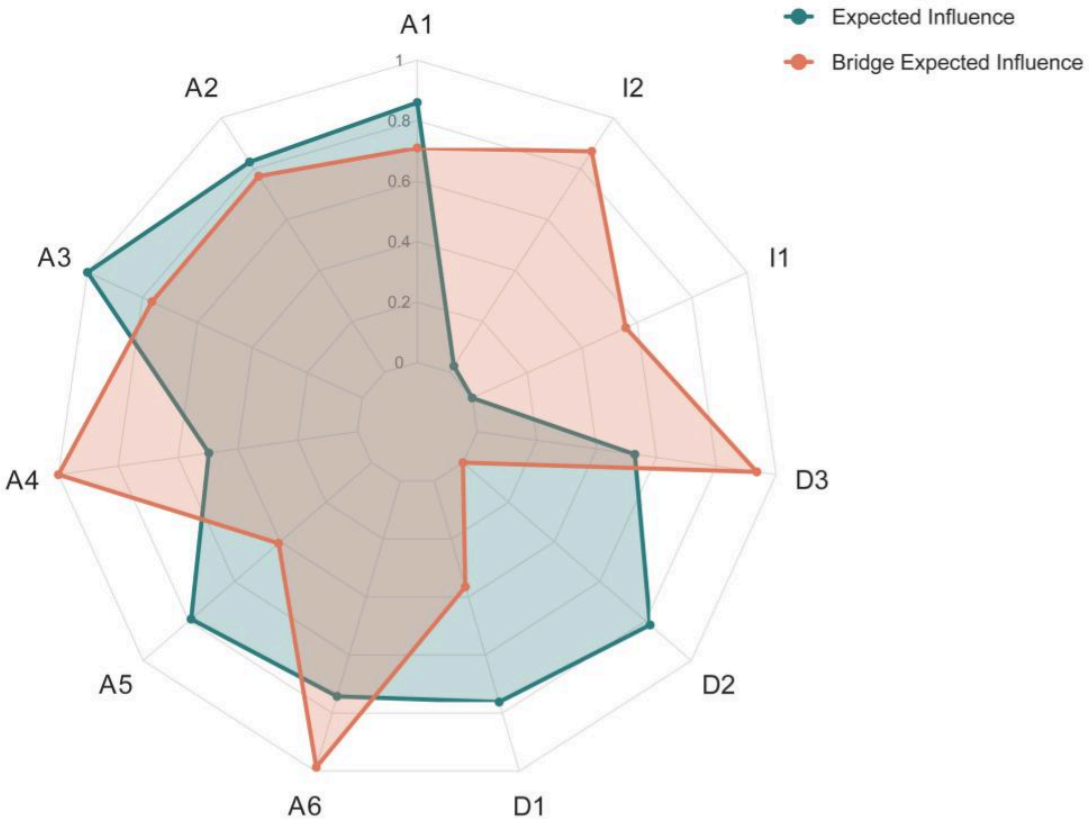


Figure 2

The EI and BEI of each node in the GGM network of negative life events, psychological resilience and theory of mind.

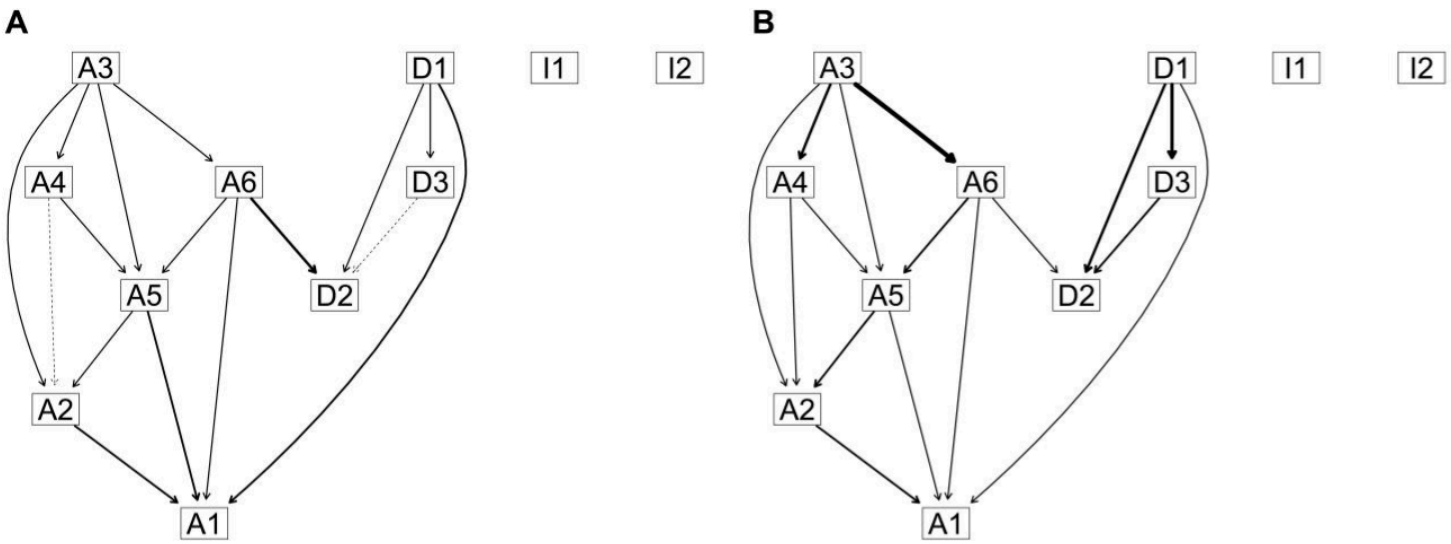


Figure 3

The DAG structure among negative life events, psychological resilience, and each dimension of theory of mind. ***Note.*** Figure 3A shows the direction probability graph, where the thickness of the edges reflects the direction probability of that direction in all the bootstrapping-generated networks. The thicker the edge, the greater the probability of the causal direction between the variables; Figure 3B shows the structural contribution graph, where the thickness of the edges indicates their importance to the overall DAG structure. The thicker the edge, the greater the contribution of that edge to the model fitting. Together, these two present the causal inference relationship between the variables.

Supplementary Files

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