

The longitudinal effect of psychological distress on internet addiction symptoms among Chinese college students: a cross-lagged panel network analysis

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Abstract

Background: There has been growing amount of evidence suggested the high rates of co-occurring Internet addiction (IA) symptoms and psychological distress in youths. However, the extent to how IA symptoms develop over time, how IA symptoms interact with psychological distress symptoms dynamically and how these symptoms predict each other remains unclear. Additionally, which specific distress including depressive, anxious, stress symptoms are more closely associated with IA symptoms remains inconclusive.

Objective: This longitudinal study aims to explore the development and changes of IA symptoms over time and the directional relationship between IA and various psychological distress.

Methods: This study followed a sample of 2,497 Chinese college students (M age = 19.14 years) across three waves of data collection span two years. Their IA and psychological distress symptoms were assessed at baseline (T1), 12-month follow-up (T2) and 24-month follow-up (T3). We employed network analysis to examine the network structure of IA symptoms at each wave, and cross-lagged panel network analysis (CLPN) to investigate longitudinal associations between IA symptoms and psychological distress including depressive, anxious and stress symptoms.

Results: The cross-sectional networks of IA symptoms at three time points showed high similarity in terms of structure, existence of edges, and centrality indices. Nodes A2 ('excessive use'), A1 ('salience'), and A5 ('lack of control') emerged as the nodes with the highest expected influence centrality (EI) in the IA symptom networks across time (A2, EI=1.13 at T1, 1.15 at T2, 1.17 at T3; A1, EI=1.10 at T1, 1.13 at T2, 1.15 at T3; A5, EI=0.86 at T1, 0.88 at T2, 0.92 at T3). CLPN revealed that psychological distress predicted IA symptoms, but not the other way around. Depressive symptoms played a key role in predicting various IA-related problems (T1?T2, edge weight = 0.11; T2?T3, edge weight = 0.28; T1?T3, edge weight = 0.22), and may also serve as bridge symptoms connecting IA and psychological distress issues (T1?T2, Bridge-EI = 0.15; T2?T3, Bridge-EI = 0.14; T1?T3, Bridge-EI = 0.19).

Conclusions: Findings revealed a relatively stable network structure of IA symptoms among college students and suggested that psychological distress, especially depressive symptoms, may play a central role in activating IA symptoms over time. These results provide evidence for understanding the directional relationship between the central characteristics of distress symptoms and IA. The current study also underscores the importance of depressive symptoms in their co-occurrence with IA, indicating that the key and bridge symptoms identified in this study can be prioritized as targets for preventing and treating IA in Chinese youth. Through identification and early intervention of depressive symptoms, we may avoid the progression of co-occurring issues, leading to more effective treatment outcomes.

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Original Manuscript

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06/04/2025

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Conclusion: Findings revealed a relatively stable network structure of IA symptoms among college students and suggested that psychological distress, especially depressive symptoms, may play a central role in activating IA symptoms over time. These results provide evidence for understanding the directional relationship between the central characteristics of distress symptoms and IA. The current study also underscores the importance of depressive symptoms in their co-occurrence with IA, indicating that the key and bridge symptoms identified in this study can be prioritized as targets for preventing and treating IA in Chinese youth. Through identification and early intervention of depressive symptoms, we may avoid the progression of co-occurring issues, leading to more effective treatment outcomes.

Keywords: Internet addiction; Depression; Anxiety; Stress, Cross-lagged panel network analysis

Introduction

The Internet has brought numerous benefits to young generations, such as facilitating online communication and providing easy access to educational resources [1]. However, it has also given rise to a growing concern in global public health -- Internet addiction (IA) [2]. IA refers to “excessive or poorly controlled preoccupations, urges or behaviors regarding computer use and Internet access that lead to impairment or distress” [3]. College students, in particular, have become a focal point within the broader Internet user population. The pooled prevalence of IA was estimated to be around 11% among college students in China [4-6]. Given the high prevalence, negative impact, and changing nature of IA in this group, it is crucial to enhance our understanding of IA in college students in order to develop effective early intervention strategies [7].

College students are experiencing a critical developmental period marked by drastic physical, psychological, and biological changes [8]. Additionally, as students transition to college, their living environment undergoes significant changes. With more free time, less supervision, and easier access to the Internet, many students may become more prone to excessive online use. These environmental and psychological shifts increase the risk of Internet addiction (IA) among college students [9]. Many previous studies have investigated the prevalence, persistence, and correlates of IA in college students [4, 10, 11]. However, problematic Internet use is a dynamic process with fluctuating patterns over time. More research is needed to investigate the robust developmental characteristics of Internet addiction. Therefore, a long-term study investigating these patterns may provide clearer insights into the development and trajectory of IA symptoms in this population.

It was also worth noticing that IA symptom is rarely an isolated issue. To date, a significant body of studies have found the co-occurrence or the correlations of IA with various psychological distress including stress, depression, and anxiety [12-15]. However, two key questions remain regarding the relationship between psychological distress and IA symptoms. First, the directional relationship between IA symptoms and psychological distress was not fully understood. Various studies and theory models yielded inconsistent conclusions regarding the directional relationship between IA symptoms and psychological distress. The Cognitive-Behavioral Model of Pathological Internet Use posits that negative emotions lead to maladaptive cognitions for internet use, thereby resulting in IA [16]. The theory of compensatory Internet use suggests that individuals with depressive symptoms tend to develop certain internet use motivations such as escaping reality through internet use to alleviate their depressive symptoms [17]. The Interaction of Person-Affect-Cognition-Execution Model also suggests that individuals with negative emotions are more likely to experience negative emotional or cognitive reactions (e.g., craving to regulate mood through addictive substances) when faced with tempting or stressful situations. This can lead to Internet addiction [18]. Despite their divergent foundations in maladaptive cognitions, psychological resource theory and neurobiological processes, all three models converge in identifying negative emotions as predisposing factor for IA. Many empirical studies have provided support for these theories, as they found that individuals with psychological distress are more likely to develop IA [20-23].

On the other hand, some research suggested that addictive disorders might precipitate other psychiatric disorders [24]. Specifically, individuals with addictive behaviors tend to spend more time and energy on the Internet and experience frustration or depression when returning to real-life demands [25, 26]. There were also studies proposed a bidirectional relationship, where IA and other psychiatric disorders may mutually increase susceptibility [27, 28]. Yet, the existing data supporting these hypotheses remain inconclusive.

Whether IA symptoms trigger psychiatric distress, or the reverse, is still unclear. Existing research has several limitations. First, most studies have relatively short follow-up periods, which makes it challenging to capture the full scope of changes and instability in IA symptoms and their co-occurrence with negative emotional symptoms. Thus, further studies with longer tracking periods are needed to test these questions more comprehensively. Second, previous research had mostly relied on latent variable models [33, 34], which are limited in their ability to explore IA symptoms and their

relationship to specific types of distress at the item level. In other words, the specific associations between different forms of psychological distress and IA remain unclear. Some studies suggest that depressive symptoms may have a stronger correlation with IA compared to stress and anxiety [12, 37], while other researchers found a stronger correlation between anxiety and IA [37]. Further investigation into how different aspects of distress specifically interact with IA symptoms is needed, as this could help identify precise risk factors and inform targeted interventions for co-occurring issues, which are crucial for improving health outcomes among college students.

Related studies provided limited insight into the changes of IA symptoms and its relationship with different distress may be related to the restrict of the method used. Network analysis, based on the network theory of mental disorders, allows for the visualization of different symptoms within a network, helping to assess their complex relationships and interactions at the symptom level [38, 39]. In addition to constructing cross-sectional networks, cross-lagged panel network (CLPN) analysis is commonly used with multi-wave longitudinal data to explore the dynamics within and between psychological constructs over time. CLPN helps identify the most central symptoms in terms of their predictive relationships, revealing which symptoms influence others or are influenced by them. Given these strengths, the current study employs network analysis as the primary statistical approach.

To sum up, this longitudinal study aims to explore (1) the development and changes of IA symptoms over time, (2) the directional relationship between IA and psychological distress, and (3) the distinct effects of various aspects of psychological distress on IA symptoms. To address these questions, three cross-sectional IA symptom networks and three cross-lagged panel network models were constructed. The findings of this study could provide valuable insights into the progression of IA symptoms and the specific patterns of interaction between IA and psychological distress, helping to identify key targets for intervention strategies.

Materials and methods

Participants and procedure

Participants in this study were recruited from a university in Hunan province, China. Three waves of surveys were conducted between 2019 and 2021. During the 2019–2020 academic year, all 3,800 freshmen were invited to participate in the baseline survey in December 2019. Survey details were provided on the questionnaires and distributed to students during a class break. Written informed consent was obtained from all participants before they completed the measures. Ultimately, 3,578 freshmen agreed to participate and completed the questionnaires at T1 (October 2019). In 2020, due to the rapid spread of the virus, the university was closed, and all students were placed in quarantine to protect public health. Consequently, an online survey was conducted through the 'Questionnaire Star' platform for the second wave in June 2020, with 3,205 students completing the survey. The third wave of data collection took place in December 2020, after the epidemic had been better controlled, and on-site surveys resumed. A total of 2,953 students completed the third wave survey. Missing data were handled using multiple imputations with the 'mice' package in R. [40]. All participants were informed about the study's purpose and procedures and provided written informed consent. Ultimately, 2,497 students who completed the questionnaires across all three waves were included in the final analysis. At each time point (T1–T3), self-report questionnaires covering demographics, psychological distress, and IA were administered during a class break. The study was approved by the ethics committee of The Second Xiangya Hospital of Central South University.

Psychological Assessments

Internet addiction

IA symptoms were measured using Young's Internet Addiction Test (IAT) [41]. The IAT includes 20 items rated on a 5-point Likert scale, from 1 (rarely) to 5 (always), with total scores ranging from 0 to 100. Higher scores indicate a greater level of IA. The Chinese version of the IAT

has been previously validated [42, 43]. In this study, the Cronbach's α , were 0.87 for T1, 0.89 for T2, and 0.90 for T3. The internal consistencies of six factors are shown in Supplementary Table S1. Confirmatory factor analyses were performed to confirm the construct validity of the IAT. The one-factor model and the classical six-factor model (salience, excessive use, neglect work, anticipation, lack of control, neglect social life) proposed by Widyanto and his colleague [44] were both evaluated. The models demonstrated good fit at all time points, as indicated in Supplementary Table S2.

Psychological distress

The distress experiences were measured by Depression Anxiety Stress Scales (DASS) which consists of 21 items divided into three subscales, with 7 items each, measuring depression, anxiety, and stress [45]. Items were rated on a 4-point Likert-type scale, ranging from 0 (did not apply) to 3 (applied most of the time). Total scores for each dimension are obtained by summing the item scores of the subscales, with possible totals ranging from 0 to 21 for each of the three factors. At Time Point 1, the Cronbach's α was 0.93, while at Time Points 2 and 3, the Cronbach's α reliability was 0.95 for both.

Statistical analyses

The mean scores (M) and standard deviations (SD) for the IAT and DASS across the three waves were calculated using IBM SPSS Statistics (Version 27). Network analysis was conducted using R Studio (Version 4.2), encompassing network estimation, network comparison, and cross-lagged panel networks. Missing data were addressed through multiple imputations using the 'mice' commands from the R package mice [40].

Network estimation

To estimate IA network structures at each wave, the EBICglasso function from the qgraph package (Version 1.5) was used. Once network models are estimated for each time point, node centrality and edge weights were assessed. Centrality was measured by the index of 'Expected influence' (EI), which quantifies how strongly and directly a symptom node was associated with all other nodes in the network. Edge weights were numerical values assigned to edges representing regularized partial correlations in networks.

The accuracy, stability and reproducibility of IA networks

The accuracy, stability and reproducibility of the IA network structures was assessed by using the 'bootnet' package (Version 1.1.0) with a bootstrapping procedure with 1200 iterations. First, the accuracy of the edge through the 95% confidence interval (CI) of the bootstrapped edge weight were estimated. When the bootstrapped CIs are wide, it becomes hard to assure the stability of an edge. Second, the stability of the node centrality was tested by subset bootstrapping. The centrality stability coefficient (CS coefficient) was adopted as a reference index. For the CS coefficient, values greater than or equal to 0.25 indicated acceptable stability, and values greater than or equal to 0.5 indicated good stability. In addition, edge weights difference tests and centrality difference tests were conducted to assess whether differences between edge weights or node centralities were statistically significant. Lastly, to estimate the power, the netSimulator function was used to simulate data under a given network model and expected network structure. Epskamp proposed three properties including sensitivity, specificity and the correlation between edge weights of the true network and those of the estimated network in the exploration of an appropriate sample size to detect true effect sizes [39]. The three properties should be high in the appropriate sample. Results of all these edge weights accuracy, correlation stability, bootstrapped difference tests, and power analysis can be found in the supplementary materials. (See in Supplement Materials).

Network comparison

The network comparison test in the R package 'NetworkComparisonTest' (NCT) was used to examine the IA network structure difference over time through a permutation test [46]. Network

invariance, global strength, and edge weights were calculated to describe differences in the global and local characteristics of IA networks.

Cross-lagged panel networks

In order to examine prospective associations between IA symptoms and psychological distress, three cross-lagged panel networks (CLPN) (T1→T2, T2→T3, T1→T3) were computed. In the networks, the 21 items of the DASS were used as individual nodes representing psychological distress symptoms and the 6 sub-dimensions of Young's Internet Addiction Test were used as nodes representing IA symptoms. This factor-item approach reduced data dimensionality while preserving crucial sub-dimension information. It also ensured a balanced number of IA symptom and distress nodes, meeting the node equilibrium requirements for network analysis [39].

The 'glmnet' package [47] and the 'qgraph' package were used to calculate regressions and plot all graphs of CLPN, respectively. In CLPN, variable contributions are represented as both autoregressive effects and cross-lagged effects, which quantified by a series of regularized regressions and the penalized maximum likelihood with the LASSO penalty. We set the tuning parameter ($\lambda = 0.5$) to increase the sparsity of a graph and reduce the possibility of overfitting problems. This calculation allows for the estimation of CLPN centralities for in-prediction, out-prediction, and bridge items, thereby clarifying the directed relationships between IA and distress. Specifically, in-prediction was estimated by index of In-expected influence (IEI), which reflects the proportion of variance in a node at T2 explained by variables at T1. Out-prediction was estimated by out-expected influence (OEI), which reflects the influence of a node at T1 on variables at T2. In this study, we focused on cross-construct network centralities, excluding paths within the same construct, to better clarify the longitudinal interactions between IA and psychological distress. Additionally, one-step and two-step bridge expected influence (BEI1 and BEI2) were calculated to identify bridge items linking IA symptoms with psychological distress.

Post hoc stability and accuracy analysis of CLPN

The accuracy and stability of CLPN was also estimated using two bootstrapping approaches implemented by the R package 'bootnet'. First, we calculated 95% confidence intervals (CIs) for edge weight accuracy via nonparametric bootstrapping (1200 bootstraps) to estimate the network stability [39]. Second, the stability of the rank-order of centrality indices and edges were examined by computing the correlation stability (CS) coefficient [39].

Results

Descriptive analysis

An independent-samples t-test revealed no significant differences in study variables (IAT and DASS) between participants who completed all three waves and those who dropped out ($t = 1.87/1.52$, $p = 0.062/0.128$), indicating that data were missing at random. The final sample included 2,497 participants who completed assessments across all three waves, comprising 29.1% male and 70.8% female participants, with ages ranging from 16 to 22 years ($M = 19.14$, $SD = 0.72$) and education ranging from 11 to 15 years ($M = 12.34$, $SD = 0.71$). Of the final participants, 42.7% grew up in urban areas, and 52.4% grew up in rural areas before age 12. Table 1 presents item descriptions, node labels, and the means of psychological distress and IA symptoms.

Table1 Item labels and descriptive statistics (N=2497)

Item		Label	T1		T2		T3	
			<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Internet	Addiction		44.92	13.9	43.35	14.75	43.8	15.12
Test				6			6	

salience	A1	11.42	4.08	10.96	4.13	11.0	4.22
excessive use	A2	10.87	3.78	10.64	3.89	10.8	3.99
neglect work	A3	7.26	2.69	6.85	2.79	6.87	2.79
anticipation	A4	4.28	1.83	4.32	1.84	4.47	1.93
lack of control	A5	7.19	2.99	6.66	2.87	6.71	2.86
neglect social life	A6	3.94	1.78	3.97	1.68	3.94	1.69
Depression Anxiety							
Stress Scales		11.27	9.49	9.00	9.44	9.13	9.80

NOTE: Six factors of the Internet addiction test are namely salience, excessive use, neglect work, anticipation, lack of control, neglect social life and we use these factors as nodes of networks.

Dynamic changes of IA networks

Network of IA symptoms

Figure 1 present the IA symptom networks and centrality plots for T1, T2, and T3. The symptom networks across these three time points were similar. Notably, the edge between A2 ('excessive use') and A5 ('lack of control') consistently showed the highest weight across all three networks. Nodes A2 ('excessive use'), A1 ('salience'), and A5 ('lack of control') demonstrated the highest expected influence (EI) values at each time point (T1: A2, EI=1.13; A1, EI=1.10; A5: EI=0.86; T2: A2, EI=1.15; A1, EI=1.13; A5: EI=0.88; T3: A2, EI=1.17; A1, EI=1.15; A5: EI=0.92). The results of the bootstrapped difference tests for edges and expected influence are presented in Supplementary Figure S3.

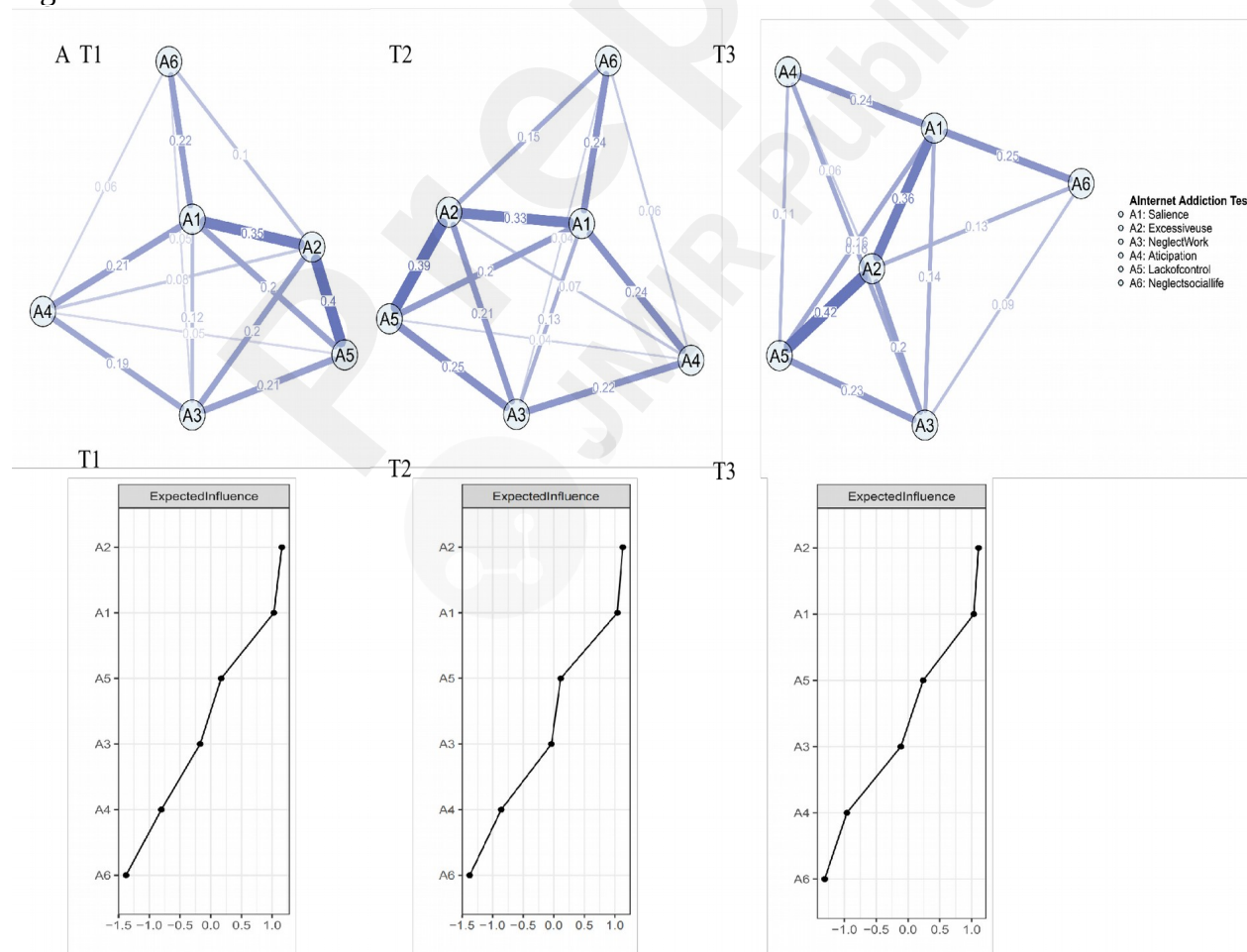


Fig. 1. Internet addiction symptom networks of three waves

Network comparison of IA networks

We compared edge strength, global strength, and network invariance between the networks at T1 and T2, as well as T2 and T3. The results indicated no significant differences in edge strength between T1 and T2 ($p = 0.17$) or between T2 and T3 ($p = 0.15$). However, a significant global difference was observed between T1 and T2 (global strength T1/T2 = 2.44/2.57, $S = 0.13$, $p = 0.01$), but not between T2 and T3 (global strength T2/T3 = 2.57/2.56, $S = 0.01$, $p = 0.69$). Additionally, no significant differences in network invariance were found between T1 and T2 ($M = 0.05$, $p = 0.64$) or between T2 and T3 ($M = 0.06$, $p = 0.39$).

Potential effect of psychological distress on IA symptoms: cross-lagged panel networks

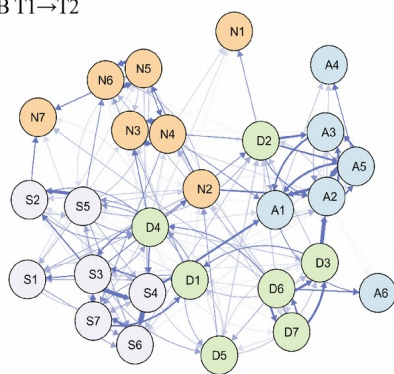
To further analyze the longitudinal associations between psychological distress and IA symptoms across shorter and longer time cycles, we established three cross-lagged panel networks for T1→T2, T2→T3, and T1→T3 (Figure 2). To enhance the visual interpretability of the cross-lagged edges, we excluded the autoregressive edges, as the plotting algorithm scales path thickness relative to the strongest path. After achieving regularization convergence and omitting the autoregressive paths, we identified 186 non-zero cross-lagged edges in the T1→T2 network, 195 in the T2→T3 network, and 160 in the T1→T3 network. A plot that includes these weaker edges can be found in Supplementary Figure S4.

In the cross-lagged panel networks for T1→T2 (Figure 2), the strongest cross-lagged edge reflecting the longitudinal processes within IA symptoms was from A5 to A2 ('lack of control' to 'excessive use'; edge weight = 0.14). Within psychological distress symptoms, the strongest edge was from S4 to S6 ('I found myself getting agitated' to 'I was intolerant of anything that kept me from getting on with what I was doing'; edge weight = 0.14). When examining the longitudinal effects between IA and psychological distress, the most significant cross-lagged edges were from D3 to A2 ('I felt that I had nothing to look forward to' to 'excessive use'; edge weight = 0.11) and from D2 to A3 ('I found it difficult to work up the initiative to do things' to 'neglect work'; edge weight = 0.11). The three strongest out-expected influence (OEI) nodes (Figure 3) were D4 ('I felt down-hearted and blue'; OEI = 1.53), S3 ('I felt that I was using a lot of nervous energy'; OEI = 1.36), and S5 ('I found it difficult to relax'; OEI = 1.24). Three strongest in-expected influence (IEI) nodes (Figure 3) were A2 ('excessive use'; IEI = 2.70), A1 ('salience'; IEI = 2.08), and S6 ('I was intolerant of anything that kept me from getting on with what I was doing'; IEI = 1.31). Finally, the three strongest bridge-expected influence (BEI) nodes (Figure 4) were D4 ('I felt down-hearted and blue'; BEI = 0.15), D6 ('I felt I wasn't worth much as a person'; BEI = 0.14), and D7 ('I felt that life was meaningless'; BEI = 0.11).

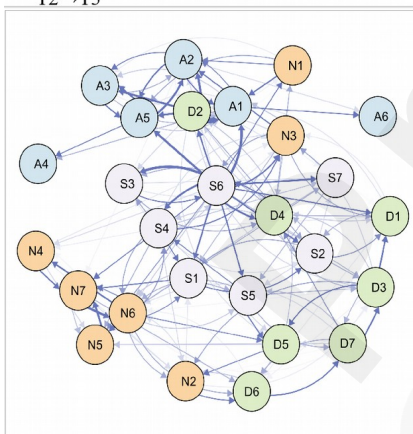
In the T2→T3 network (Figure 2), the strongest cross-lagged edge within IA symptoms was from A5 to A2 ('lack of control' to 'excessive use'; edge weight = 0.11), while within psychological distress symptoms, it was from N6 to N5 ('I was aware of the action of my heart in the absence of physical exertion' to 'I felt I was close to panic'; edge weight = 0.17). Regarding the longitudinal effects between IA and psychological distress, the most significant cross-lagged edges were from D2 to A1 ('I found it difficult to work up the initiative to do things' to 'salience'; edge weight = 0.28) and from S6 to A1 ('I found it difficult to work up the initiative to do things' to 'salience'; edge weight = 0.13). The three strongest out-expected influence (OEI) nodes (Figure 3) were S6 ('I was intolerant of anything that kept me from getting on with what I was doing'; OEI = 4.18), D2 ('I found it difficult to work up the initiative to do things'; OEI = 1.78), and N6 ('I was aware of the action of my heart in the absence of physical exertion'; OEI = 1.15). The three strongest in-expected influence (IEI) nodes (Figure 3) were A1 ('salience'; IEI = 3.30), A2 ('excessive use'; IEI = 1.65), and A5 ('lack of control'; IEI = 1.49). Lastly, the three strongest bridge-expected influence (BEI) nodes (Figure 4) were S6 ('I was intolerant of anything that kept me from getting on with what I was doing'; BEI = 0.56), S4 ('I felt I wasn't worth much as a person'; BEI = 0.15), and D7 ('I felt that life was meaningless'; BEI = 0.14).

In the T1→T3 network (Figure 2), the strongest cross-lagged edge within IA symptoms was from A5 to A3 ('neglect work'; edge weight = 0.07). Among psychological distress symptoms, the strongest edge was from S4 to S6 ('I found myself getting agitated' to 'I was intolerant of anything that kept me from getting on with what I was doing'; edge weight = 0.14). The most significant cross-lagged edges between IA and psychological distress were from D4 to A2 ('I felt down-hearted and blue' to 'excessive use'; edge weight = 0.22) and from D4 to A1 ('I felt down-hearted and blue' to 'salience'; edge weight = 0.21). The three strongest out-expected influence (OEI) nodes (Figure 3) were D4 ('I felt down-hearted and blue'; OEI = 3.32), S4 ('I found myself getting agitated'; OEI = 1.78), and N5 ('I felt I was close to panic'; OEI = 1.52). The three strongest in-expected influence (IEI) nodes (Figure 3) were A1 ('salience'; IEI = 3.26), A2 ('excessive use'; IEI = 2.37), and A5 ('lack of control'; IEI = 0.86). The three strongest bridge-expected influence (BEI) nodes (Figure 4) were N5 ('I felt I was close to panic'; BEI = 0.20), S3 ('I felt that I was using a lot of nervous energy'; BEI = 0.20), and D4 ('I felt down-hearted and blue'; BEI = 0.19). The results of the bootstrapped difference tests for edges, out-expected influence, in-expected influence, and bridge-expected influence across the three cross-lagged panel networks are presented in Supplementary Figure S5.

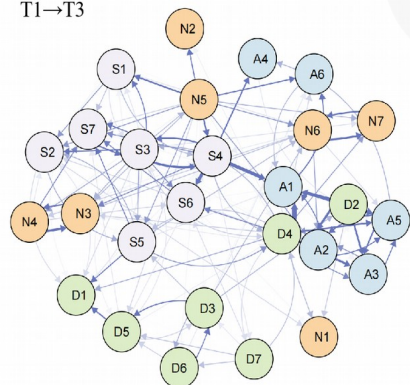
B T1→T2



T2→T3



T1→T3



- Internet Addiction Test
- Anxiety
- Depression
- Stress

Internet Addiction Test

- A1: Salience
- A2: Excessiveuse
- A3: NeglectWork
- A4: Aticipation
- A5: Lackofcontrol
- A6: Neglectsociallife

Stress

- S1: I found it hard to wind down
- S2: I tended to over-react to situations
- S3: I felt that I was using a lot of nervous energy
- S4: I found myself getting agitated
- S5: I found it difficult to relax
- S6: I was intolerant of anything that kept me from getting on with what I was doing
- S7: I felt that I was rather touchy

Anxiety

- N1: I was aware of dryness of my mouth
- N2: I experienced breathing difficulty
- N3: I experienced trembling
- N4: I was worried about situations in which I might panic and make a fool of myself
- N5: I felt I was close to panic
- N6: I was aware of the action of my heart in the absence of physical exertion
- N7: I felt scared without any good reason

Depression

- D1: I couldn't seem to experience any positive feeling at all
- D2: I found it difficult to work up the initiative to do things
- D3: I felt that I had nothing to look forward to
- D4: I felt down-hearted and blue
- D5: I was unable to become enthusiastic about anything
- D6: I felt I wasn't worth much as a person
- D7: I felt that life was meaningless

Fig. 2. The cross-lagged panel networks. Arrows represent longitudinal relationships. Thicker edges

represent stronger relations

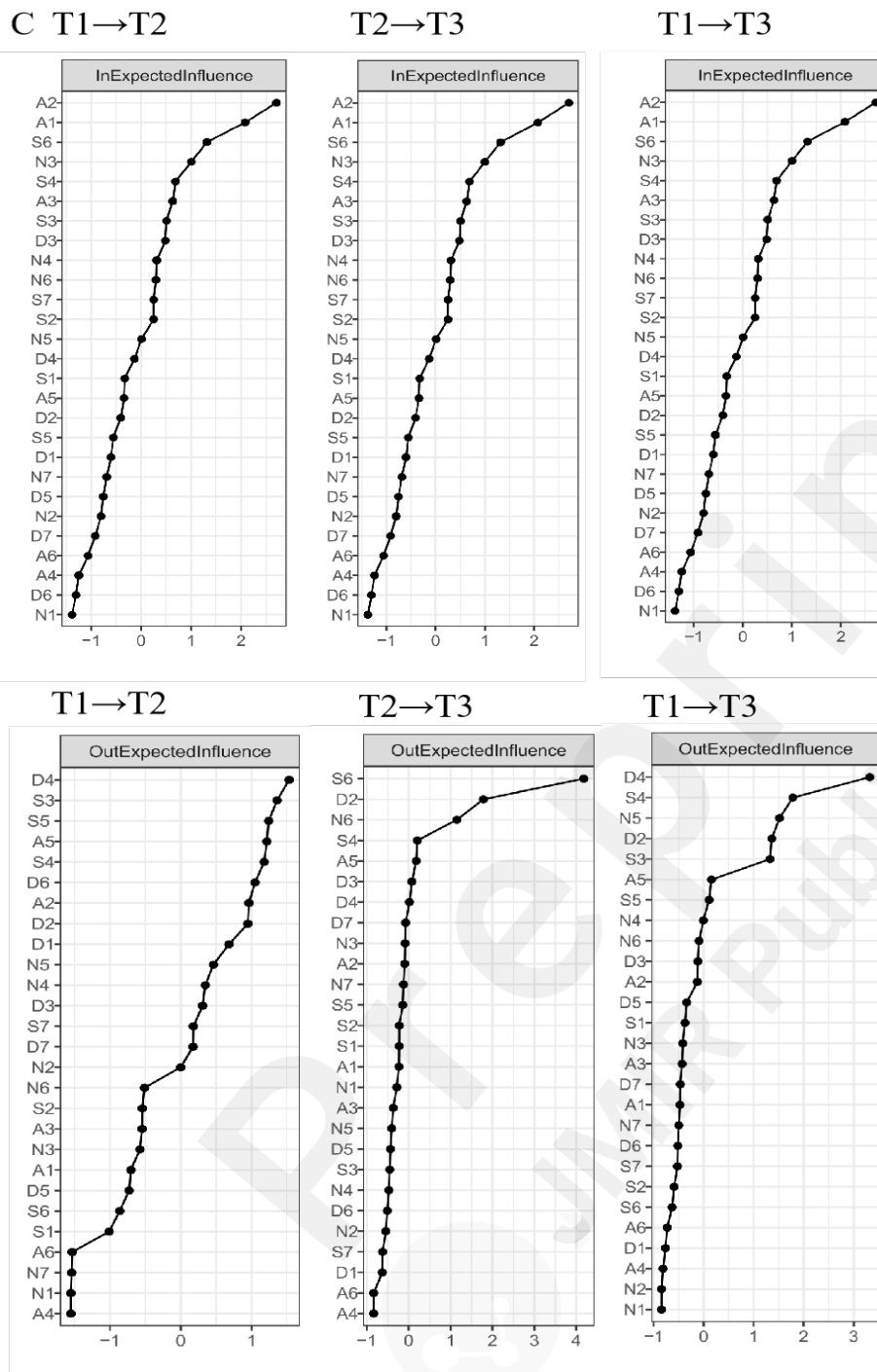


Fig. 3. The centrality plots of cross-lagged panel networks

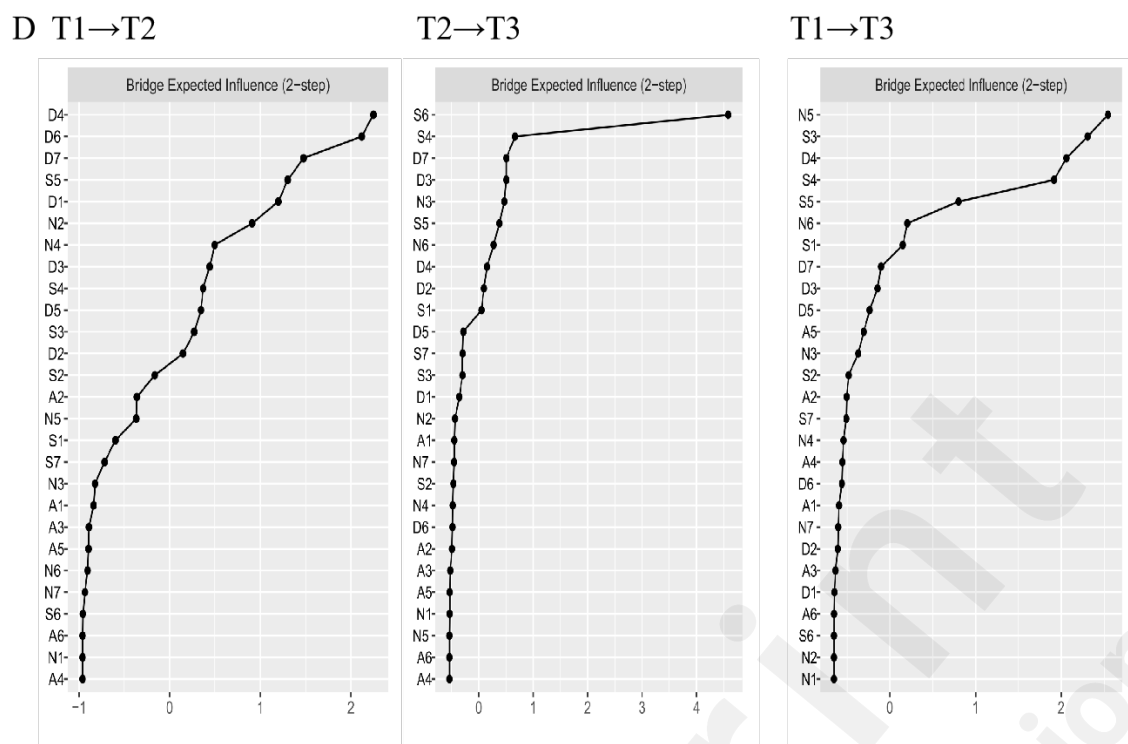


Fig. 4. The Bridge Expected Influence (2-step) plots of cross-lagged panel networks

Accuracy, stability estimation and power analysis.

The 95% bootstrapping confidence intervals (CIs) around the edge weights for the three IA networks and the CLPN networks were found to be small to moderate (Supplementary Figures S6-S7), indicating that the stability of the networks is acceptable. Additionally, the analysis of network accuracy revealed a moderate level of accuracy (detailed figures in Supplementary Figure S8). The results of the power analysis were included in the Supplementary Figure S9. And when $N=1200$, the effect of correlation, sensitivity, and specificity of the network were all acceptable (above 0.6).

Discussion

The current study investigated the development of IA symptoms and the relationship between IA symptoms and psychological distress over time by applying network analysis and CLPN approach. Central IA symptoms, such as 'excessive use', 'salience', and 'neglect work', were identified, and their dynamic changes within the networks were illustrated. Results of CLPN analysis revealed that edges with highest weights were mainly from depressive symptoms to IA symptoms across all three waves. Depressive symptoms and stress symptoms emerged as high OEI symptoms, while IA-related nodes were mostly high IEI symptoms. Furthermore, depressive symptoms, such as sadness, were found to serve as bridge symptoms. These findings illuminate the intricate connections between IA symptoms and mental health symptoms, suggesting that IA may be influenced by psychological distress, especially depressive symptoms, thus shedding light on the fundamental structure underlying these relationships.

Regarding the development of IA networks, the central symptoms and network invariance were highly similar across three cross-sectional networks. Symptoms with highest expected influence such as A1 ('excessive use'), A2 ('salience') and A3 ('neglect work') did not change with time. This provided evidence that continued excessive internet use, as a core symptom of problematic internet use, was closely related to other problematic Internet use symptoms, and are more likely to trigger other types of problematic Internet use [48]. The stable network invariance of IA also suggested that specific internet addictive behaviors may not be easily changed, which was consistent with previous studies on a large sample of Hong Kong secondary school students. Yu and his colleague also found that the addictive problem is relatively stable as opposed to wearing off over three years [49].

However, we also found that the global strength of the network of T2 was significantly higher than T1. Such pattern may mirror trends observed in other behavioral addictions (e.g., gambling, drug abuse, etc.), where behaviors typically do not decline or may even increase as individuals become more entrenched in their addiction [50]. Similarities between IA and other behavioral addiction have been widely highlighted, particularly regarding characteristics including excessive use, tolerance, withdrawal symptoms, etc. These parallels have led to calls for recognizing internet addiction as a distinct disorder [41]. Another possible explanation for the higher global strength of T2 may be the combined effects of the pandemic outbreak and academic pressure. Previous studies have noted an increase in internet addiction severity within the general population in China following the pandemic [51]. Cross-national studies also reported a higher prevalence of IA among college students during this period [52, 53]. Moreover, by their third year, college students are typically more engaged in major coursework and face challenges like securing internships, which may restrict their Internet use. Academic pressures may also diminish the appeal of Internet use among students. These hypotheses warrant further exploration through in-depth investigations, such as integrating latent profile analysis with network analysis for subgroup-specific investigations of symptom evolution patterns among populations with heterogeneous developmental trajectories.

Nodes related to psychological distress emerged as central predictive symptoms, while IA symptoms were primarily identified as symptoms being predicted. For instance, nodes D4 ('I felt downhearted and blue'), S4 ('I found myself getting agitated'), and D2 ('I found it difficult to work up the initiative to do things') exhibited high out-expected influence (OEI), whereas nodes A2 ('Salience') and A1 ('Excessive use') were identified as high in-expected influence (IEI) symptoms. This could be because excessive Internet use is often studied as a coping strategy aimed at alleviating uncomfortable emotions like loneliness, depression, and social anxiety [54]. According to the I-PACE model and compensatory Internet use theory, using the Internet to avoid negative emotions can help regulate emotions temporarily, thereby improving negative moods and providing a sense of personal and social competence [17]. When individuals feel emotionally overwhelmed, anxious, stressed, or depressed, they may have reduced capacity for conscious coping and resilience, leading them to use the Internet as an escape from reality [55]. Consequently, they may become trapped in self-destructive, addictive behaviors due to a limited ability to cope with depression, anxiety, and stress [56]. Adolescence is a critical period for developing emotional and cognitive capacities and forming lasting connections but also carries a heightened risk for behavioral addictions, such as IA, as well as gambling and eating disorders [57]. Therefore, it is essential to recognize adolescents' vulnerability to digital threats, especially IA and related mental disorders like depression [58, 59].

However, recent studies investigated the directionality of associations between psychological distress and IA found mixed results. Several longitudinal studies have clarified reciprocal relationships between IA and depressive symptoms over time among college students [33, 60]. Nevertheless, these studies were conducted at different time points from our data collection, specifically before the onset of the pandemic. Our findings provide a reflection of the directional relationship between internet addiction and mental health during the occurrence of a major public health event. Bidirectional influences might emerge in adolescents with severe IA symptoms meeting diagnostic criteria, or in clinical samples as well [61, 62]. Thus, additional studies are needed to further clarify the predictive effects between psychological distress and IA across different population samples, such as clinical samples and samples of other ages. Moreover, several studies diverged from our findings and found that IA and problematic Internet game use symptoms exhibited high out-expected influence among early adolescents, suggesting that IA symptoms could initiate other symptoms [6, 62, 63]. Such discrepancy may stem from differences in the study samples, with the earlier research examining elementary students in China, while ours involved college students who may experience distinct stressors that affect their responses to IA. This distinction highlights the importance of considering stress levels and types across age groups. To better conclude this point, we considered different forms of distress and aimed to more broadly assess the negative emotional experiences that college students might encounter, rather than focusing solely on one specific type. Through this way, we sought to explore which of the common emotional states—depression, anxiety,

or stress—is more strongly associated with problematic internet use among college students.

The present study also found that, across all three cross-lagged panel networks, the highest-weighted edges originated from the ‘depressive symptoms’ dimension to IA. Consistent with prior research, depressive symptoms demonstrated a stronger association with IA than stress or anxiety [12, 37]. This pattern is further supported by studies on specific types of Internet use. Longitudinal research examining both cross-lagged and autoregressive effects between depression and Internet Gaming Disorder (IGD) has consistently shown that depression predicts IGD in children and adolescents, whereas the reverse effect has not been observed [64-66]. Similarly, a previous longitudinal study on depression and smartphone addiction in Chinese adolescents identified a one-way predictive effect of depression on smartphone addiction, with no reverse effect [67]. These findings imply that depression may be a predictor to Internet addiction symptoms [68, 69]. A possible explanation is that during adolescence, the ability to regulate emotions is limited, resulting in adolescents being more prone to mental health problems related to IA, and depression is among the most common diseases [70, 71]. A recent government report highlighted depression as a key mental health concern among adolescents requiring intervention, while also drawing attention to the rising issue of behavioral addictions linked to Internet use in Chinese youth [72]. Building on existing research, depression is often linked to social withdrawal, diminished motivation for real-world activities, and a greater dependence on online platforms for emotional regulation or escapism, all of which may heighten the risk of IA [73]. One study also found that both depression and IA were linked to a short allele in the promoter region of the serotonin transporter gene (SS-5HTTLPR), suggesting that individuals with both conditions may share similar genetic and personality traits [74]. Our findings align with those of a meta-analysis that examined the relationship between IA and depression across a sample of individuals aged 13 to 64 years [14, 75]. Their results similarly indicated that people with depression tend to engage in more intense Internet use. In contrast, anxiety and stress, though also significant, may manifest differently in online behaviors, such as seeking reassurance or information rather than prolonged engagement [76].

Moreover, our findings revealed that depressive symptoms, particularly D4 (‘I felt downhearted and blue’), served as relatively stable bridge symptoms with high strength across all three networks. These bridge symptoms represent priority treatment targets, as their deactivation might prevent the emergence of other co-occurring symptoms [77]. This suggests an understanding of how the co-occurrence is maintained, with depressive symptoms playing a pivotal role. Past research utilizing network analysis has similarly indicated that ‘sad mood’ acts as a bridging symptom, driving young individuals toward ‘mood modification’ through short video platforms [78]. Another network analysis focusing on the co-occurrence of Internet addiction and residual depressive symptoms among adolescents identified that suicide ideation was one of the bridge symptoms across various mental disorders [79]. One possible reason for this phenomenon is that the prevalence of depressive symptoms in China is comparatively higher than the global average. Meta-analytic reviews indicated that the prevalence of depressive symptoms among Chinese adolescents rose from 24.3% before the pandemic [80] to 28.3% [81] during the pandemic. Meanwhile, depression is highly comorbid with behavioral problems such as substance abuse [82]. On the other hand, individuals suffering from depressive symptoms often seek recreational activities, including Internet use, as a means of stress relief. Internet use, particularly video gaming, is commonly regarded as an emotion-focused coping strategy [83]. Consequently, individuals experiencing depressive symptoms may turn to excessive internet use as a compensatory mechanism to mitigate their negative effect.

Implications

Our research not only enhances the theoretical framework of the problematic Internet use model [84], but also emphasizes the importance of identifying central and bridge symptoms in addressing addiction-related issues. By expanding this model, we elucidated which psychological distress factors contribute to the engagement in addictive behaviors. These findings offer valuable insights for developing effective prevention and intervention strategies for IA. Specifically, greater attention should be given to youth experiencing psychological distress, particularly depressive symptoms, as

they may turn to the Internet as a coping mechanism or avoidance strategy. It is also important to address the connection between bridge symptoms to prevent the escalation of their links to other mental health issues. When working with adolescents exhibiting problematic Internet use, incorporating an assessment of concurrent distress—especially depressive symptoms—into the treatment process is crucial and can be a cost-effective approach.

Limitations and further research

The current study had several limitations. First, it relied on self-report measures of IA and psychological distress, which may have subjective biases, such as the influence of social desirability and recall bias. Adolescents often overestimate their internet activity as well, making it challenging to obtain an objective assessment through self-report instruments [85]. Future studies could address this issue by integrating self-reported data with objective measures, such as internet usage logs or other behavioral tracking methods, to reduce potential biases. Additionally, incorporating alternative clinical assessment tools and scales could further enhance measurement accuracy. Second, the sample was drawn from a single college in China, which limits the generalizability of the findings to other populations with varying ages and experiences. However, it is worth noting that our participants represented most provincial administrative regions of China. Moreover, the IAT-20 scale used in this study does not distinguish between different types of Internet use, such as social media, web browsing, online shopping, or gaming. Future research should explore these specific subdomains and examine their distinct relationships with mental health. Finally, while our study highlighted the impact of psychological distress, particularly depression, on IA symptoms at follow-up, longitudinal studies with extended durations and multiple time waves are needed to explore common vulnerabilities and potential mechanisms in greater depth, thereby enhancing our understanding of this field.

Conclusions

This study explores the evolution of IA and the longitudinal relationships between IA symptoms and psychological distress among Chinese youth, employing network analysis and cross-lagged panel networks. The findings reveal stable central symptoms of IA—specifically, ‘excessive use’ (A2), ‘salience’ (A1), and ‘lack of control’ (A5)—among college students. Importantly, the results indicate that psychological distress predicts IA symptoms rather than the reverse. Among the various forms of distress, depressive symptoms such as ‘I felt down-hearted and blue’ (D4) and ‘I found it difficult to work up the initiative to do things’ (D2) exhibited the highest predictive effect. Furthermore, depressive symptoms may serve as bridge symptoms, linking the co-occurrence of these conditions. These results provide evidence for understanding the directional relationship between the central characteristics of distress symptoms and IA. Psychological distress, especially depressive symptoms, may play a central role in activating IA symptoms over time. The current study underscores the importance of depressive symptoms in their co-occurrence with IA, indicating that the key and bridge symptoms identified in this study can be prioritized as targets for preventing and treating IA in Chinese youth. Through identification and early intervention of depressive symptoms, we may avoid the progression of co-occurring issues, leading to more effective treatment outcomes.

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CRediT authorship contribution statement

Yuxuan Jiang: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. Chuman Xiao: Data curation, Investigation, Methodology, Visualization, Software, Writing – review & editing. Xiang Wang: Conceptualization, Investigation, Visualization, Writing – review & editing. Dongling Yuan: Methodology, Validation, Writing – review & editing. Qian Liu: Data curation, Investigation. Yan Han: Data curation, Investigation. Jie Fan: Conceptualization, Methodology, Validation, Visualization, Writing – review & editing. Xiongzhao Zhu: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that support the findings of the study are available on request from the corresponding author.

Abbreviations

IA: Internet addiction
CLPN: cross-lagged panel network analysis
IAT: Internet Addiction Test
DASS: Depression Anxiety Stress Scales
M: mean scores
SD: standard deviations
EI: expected influence
OEI: out-expected influence
IEI: in-expected influence
BEI: bridge-expected influence

Table1 Item labels and descriptive statistics (N=2497)

Item	Label	T1		T2		T3	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Internet Addiction Test		44.92	13.96	43.35	14.75	43.86	15.12
salience	A1	11.42	4.08	10.96	4.13	11.04	4.22
excessive use	A2	10.87	3.78	10.64	3.89	10.85	3.99
neglect work	A3	7.26	2.69	6.85	2.79	6.87	2.79
anticipation	A4	4.28	1.83	4.32	1.84	4.47	1.93
lack of control	A5	7.19	2.99	6.66	2.87	6.71	2.86
neglect social life	A6	3.94	1.78	3.97	1.68	3.94	1.69
Depression Anxiety Stress Scales		11.27	9.49	9.00	9.44	9.13	9.80

Figure legends

Fig. 1. Internet addiction symptom networks of three waves

Fig. 2. The cross-lagged panel networks. Arrows represent longitudinal relationships. Thicker edges represent stronger relations

Fig. 3. The centrality plots of cross-lagged panel networks

Fig. 4. The Bridge Expected Influence (2-step) plots of cross-lagged panel networks

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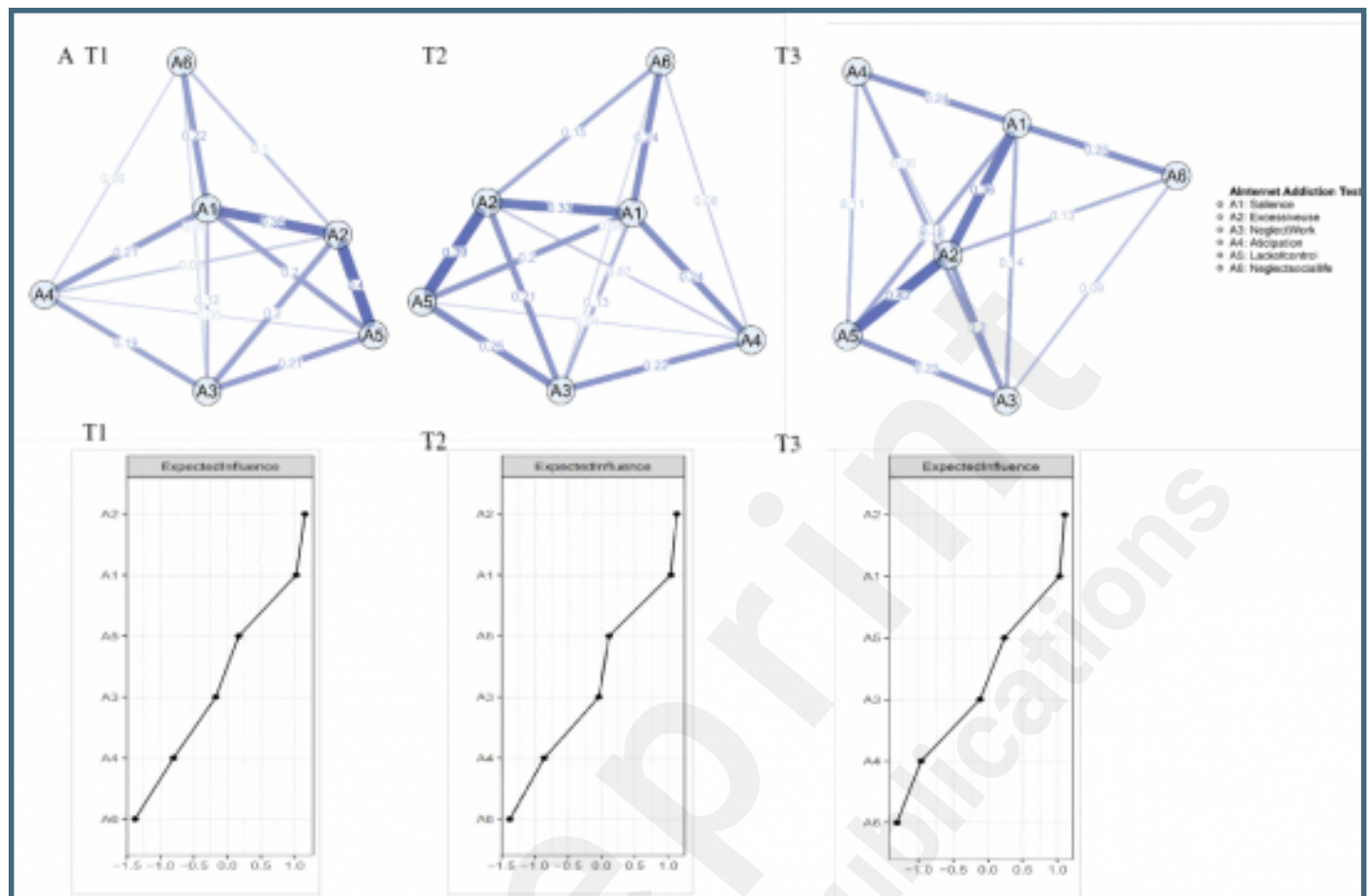
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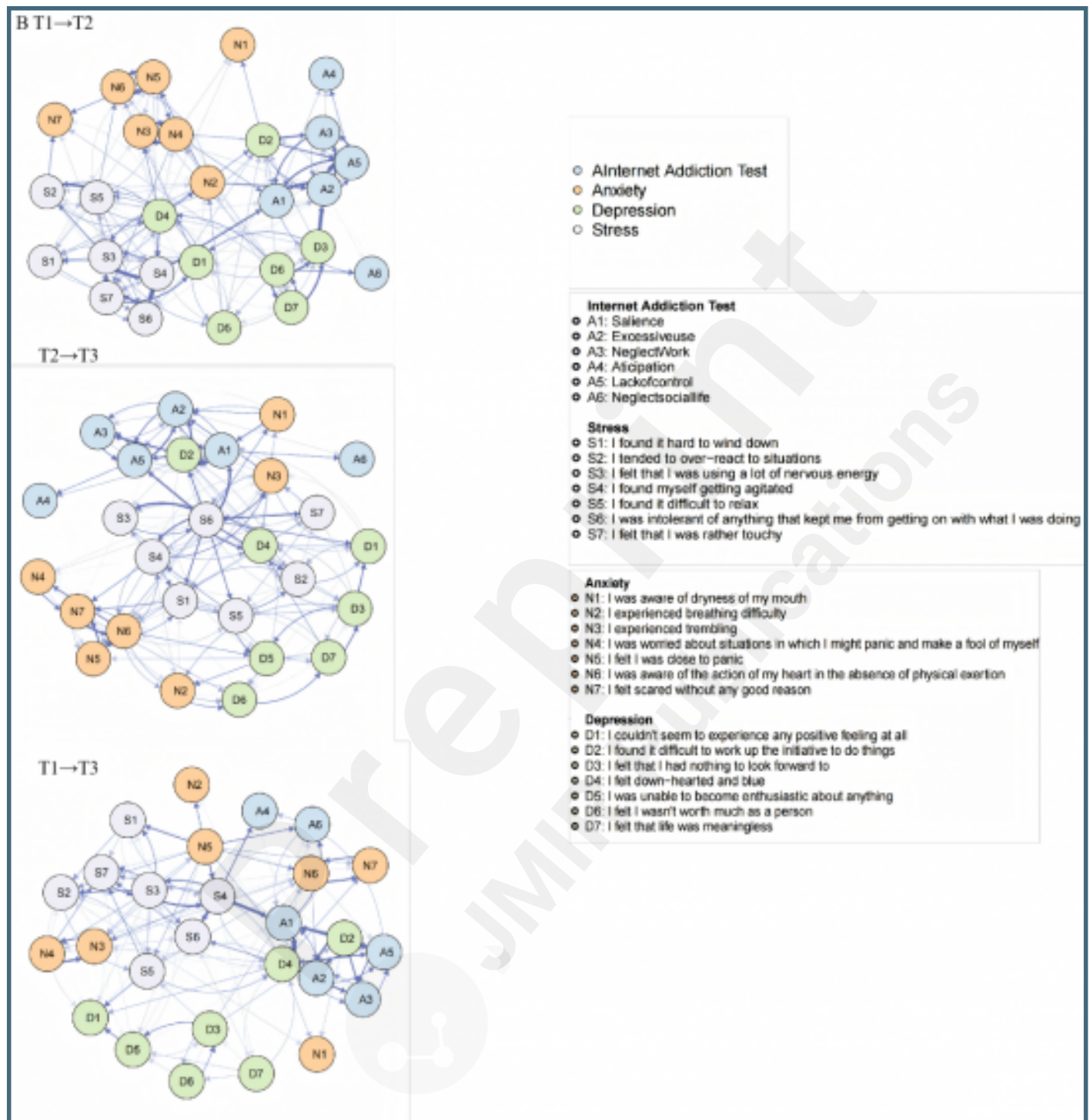
Supplementary Files

Figures

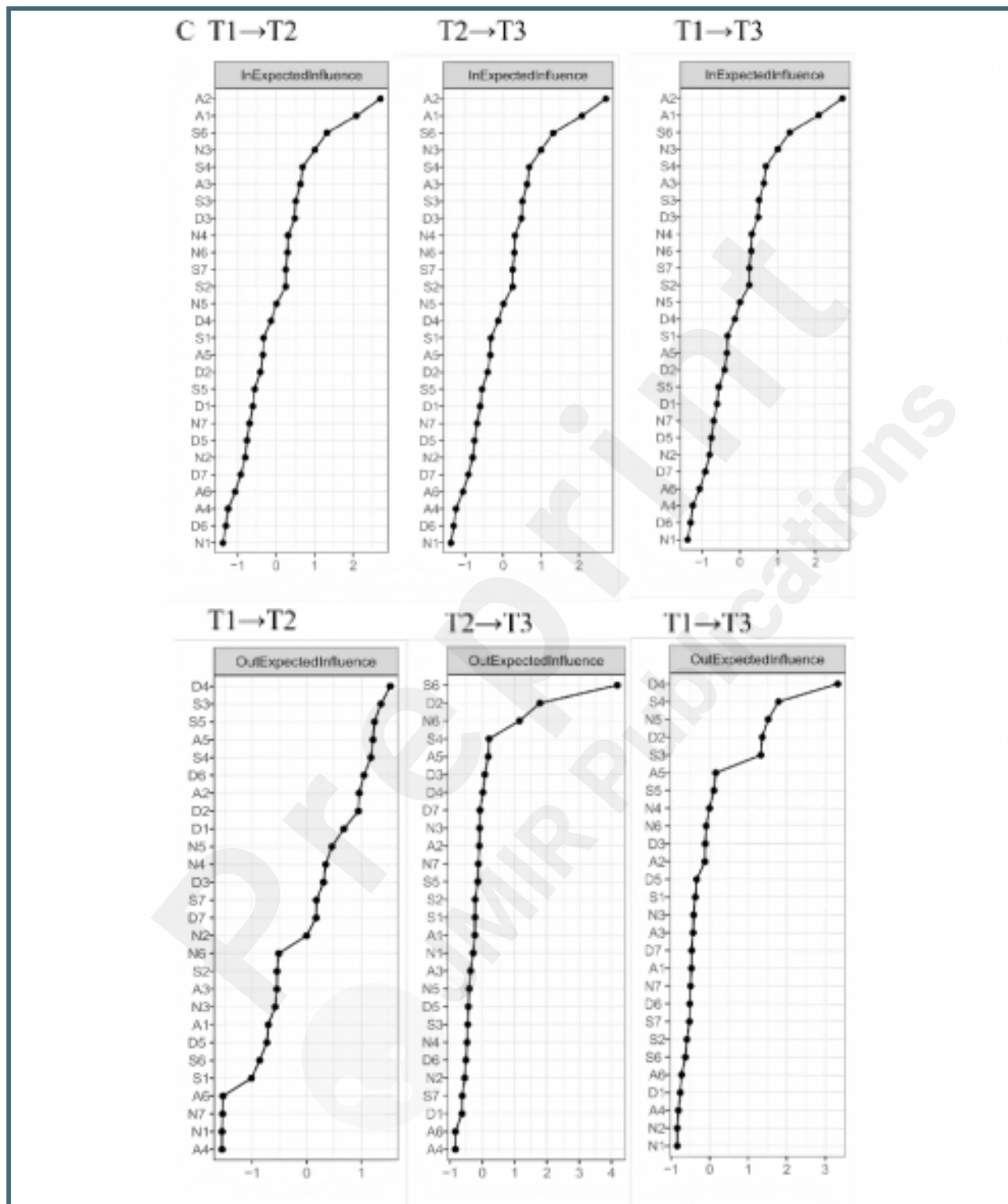
Internet addiction symptom networks of three waves.



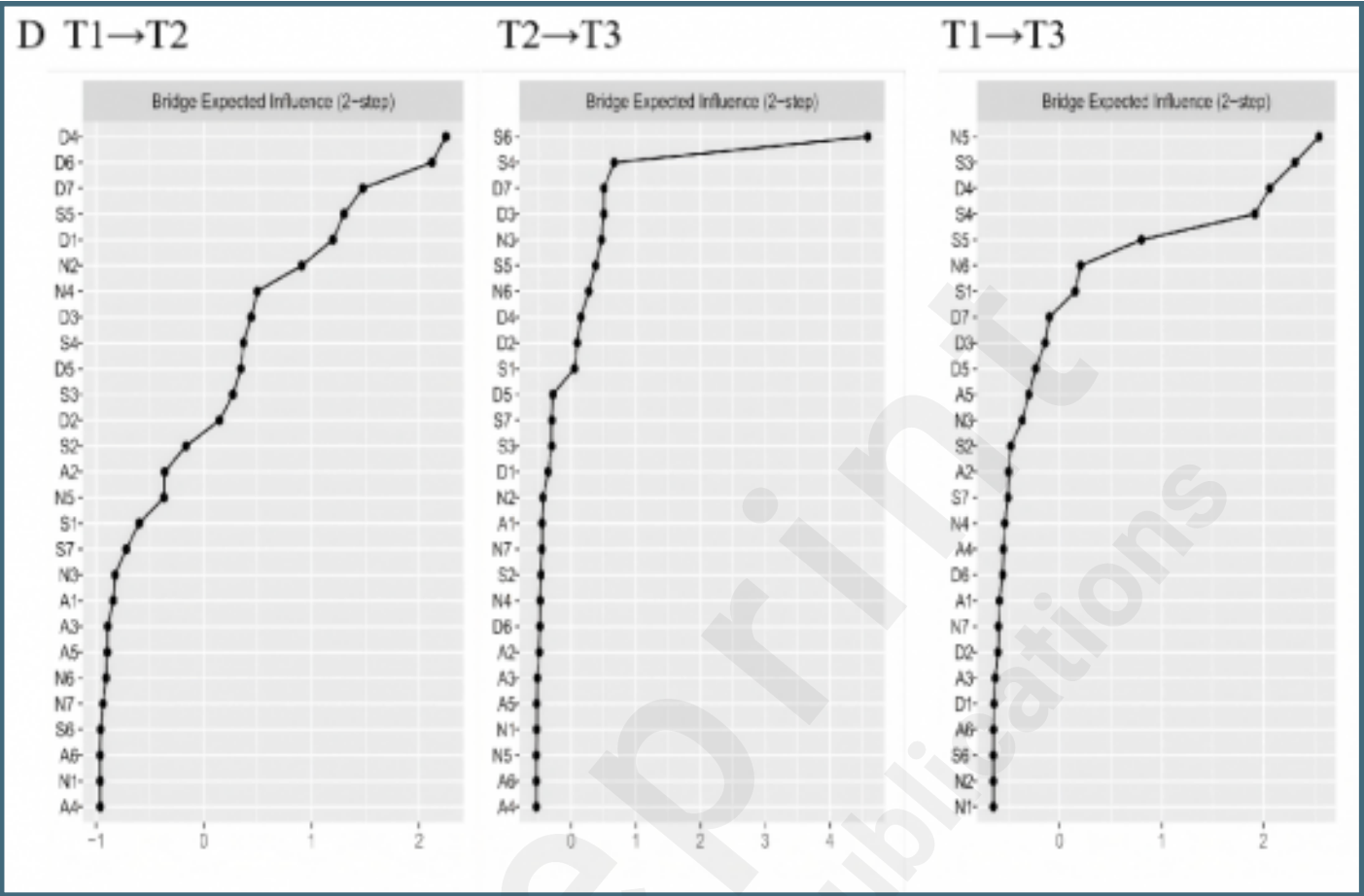
The cross-lagged panel networks. Arrows represent longitudinal relationships.



The centrality plots of cross-lagged panel networks.



The Bridge Expected Influence (2-step) plots of cross-lagged panel networks.



Multimedia Appendixes

Supplementary materials for manuscript.

URL: <http://asset.jmir.pub/assets/cf3acb5377a1c1cdc5cc74158c69de79.doc>

