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Directional Relations Between Symptoms of Adolescent Smartphone Addiction, Academic Burnout, and Psychological Distress: A Cross-Lagged Panel Network Analysis

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Background: Previous research has identified a high risk of smartphone addiction and its association with general and school-contextual mental health problems (ie, psychological distress and academic burnout) among Chinese adolescents. Nonetheless, the directional and symptom-level relationships among these problems remain underexamined, hindering understanding of the mechanisms underlying their co-occurrence. Based on the I-PACE (Interaction of Person-Affect-Cognition-Execution) model, this study addressed these gaps by performing a cross-lagged panel network (CLPN) analysis.

Methods: Data were obtained from a survey of 589 adolescents in secondary schools in China at two time points, with a five-month interval. Using a CLPN approach, this study examined the directional relationships among smartphone addiction, academic burnout, and psychological distress at the symptom level.

Results: The depression and anxiety symptoms of psychological distress, as well as the withdrawal symptom of smartphone addiction, emerged as strong bridging symptoms. Moreover, three mechanisms linking the three problems were identified. First, depression predicted cyberspace-oriented relationships and smartphone overuse, and anxiety predicted daily-life disturbances. Second, withdrawal predicted anxiety. Third, depression predicted exhaustion from studying, and withdrawal predicted cynical attitudes towards studying.

Conclusion: The results support the predisposing factors–smartphone addiction cycle described in the I-PACE model, aligning with the vulnerability, predisposition entrenchment, and intensification mechanisms proposed by the model. Psychological distress symptoms, as predisposing factors, playing key roles in the cycle. However, the results indicate that school situational factors such as academic burnout may function as distal outcomes rather than triggers in the cycle. The key linking mechanisms identified in this study are informative for generating hypotheses for future research and developing practical intervention strategies.

Keywords: smartphone addiction, academic burnout, psychological distress, cross-lagged panel network

Introduction

With the advent of the digital era, smartphones have become the most frequently used digital devices among adolescents.[1] This has resulted in concerns about smartphone addiction. Several studies have reported that the prevalence rate of smartphone addiction among secondary school students in China is around 20%.[2,3] This rate is only moderately lower than the 28% reported by a recent meta-analysis of college students.[4] Research on Chinese adolescents revealed that smartphone addiction was associated with increased academic stress, sleep delay, reduced physical activity, anxiety,

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depression, and suicidality.[5–8] These findings highlight the urgency and importance of examining smartphone addiction among adolescents.

Although smartphone addiction has not yet been categorized as a behavioral addiction in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), many researchers and practitioners have acknowledged that its characteristics are similar to those of behavioral addictions.[9–11] Smartphone addiction is typically conceptualized as a pattern of problematic smartphone use characterized by five key interrelated symptoms.[9,12] First, the symptom of daily-life disturbances refers to situations in which individuals become distracted from or neglect scheduled tasks and responsibilities due to smartphone use. Second, the symptom of withdrawal captures feelings of anxiety, irritability, or a sense of being "lost" when not holding the device. Third, the disposition of cyberspace-oriented relationships, which describes a tendency to prioritize online interactions over offline social engagement, often accompanied by frequent checking of the device to avoid missing messages or updates. Fourth, the symptom of overuse reflects difficulties in regulating smartphone use, with individuals often spending more time on the device than originally intended. Fifth, the symptom of tolerance indicates repeated unsuccessful efforts to reduce usage or an increasing need to use the smartphone more frequently in order to achieve the same level of relief or satisfaction. In network analysis of these symptoms, withdrawal appears to be the central symptom that strongly connects to other problems.[13,14] Individuals may experience an escalating cycle of these symptoms, with the overuse symptom emerging first and then progressing to symptoms of withdrawal, tolerance, and daily-life disturbances, which, in turn, further reinforce overuse.[15]

The associations between smartphone addiction and adolescents' mental health have been corroborated by many studies.[16–23] These studies have focused on general mental health, namely psychological distress, or contextual, school-related mental health—academic burnout.[24] Psychological distress is a psychological state marked by unpleasant emotions such as depression and anxiety.[25] Meanwhile, academic burnout is a psychological disorder characterized by feelings of exhaustion due to schoolwork, an indifferent attitude toward the meaning of study, and a sense of inadequacy at studying.[26] It happens when learning requirements transcend students' capacities.[27] Although academic burnout has similar symptoms with psychological distress (eg, depressed mood), it is school-related and situation-specific.[24,28] Research has also highlighted positive relationships between academic burnout and psychological distress.[29–31]

While the associations between smartphone addiction, academic burnout, and psychological distress have been revealed in existing studies, most such studies were cross-sectional in nature, making it hard to determine the direction of influence. Although some longitudinal works have been conducted to examine the directional relationships between these problems,[23,31–36] these works analyzed their associations at the aggregate level, meaning that one latent variable is used to represent each construct. The symptom-level connections between these three constructs have yet to be revealed. The neglecting of symptom-level relationships has impeded our understanding of the mechanisms underlying the comorbidity of these problems.[37,38] Moreover, while there appears to be more and more symptom-level analyses of these issues in recent years, most of these studies have focused on college students, leaving adolescents relatively underexamined.[39–41] Adolescence is a developmental stage that is particularly vulnerable to addictive behaviors as well as general and school-contextual mental health problems.[42] Therefore, this study aimed to address these research gaps by conducting a cross-lagged panel network (CLPN) analysis among Chinese adolescents and focusing on the directional relationships between these problems at the symptom level.[43,44] It not only contributes to the understanding of the mechanisms connecting these problems but also provides practical implications for intervening in these problems.

The Cycle of Smartphone Addiction, Academic Burnout, and Psychological Distress

The I-PACE (Interaction of Person-Affect-Cognition-Execution) model, a theoretical framework commonly applied to Internet-use disorders (eg, smartphone addiction), constructs a cycle of smartphone addiction, academic burnout, and psychological distress. It posits that psychopathological traits serve as core individual characteristics that predict vulnerability to developing addictive internet use behaviors, including smartphone addiction. Within these psychopathological features, depression and anxiety, as key symptoms of psychological distress, are highlighted as particularly salient predictors of smartphone addiction susceptibility (see Figure 1, Path A).[45,46]

Individuals with such predispositions (ie, psychological distress), when confronted with situational triggers that elicit biased cognitive or negative affective responses (eg, academic burnout), may experience intensified psychological stress,

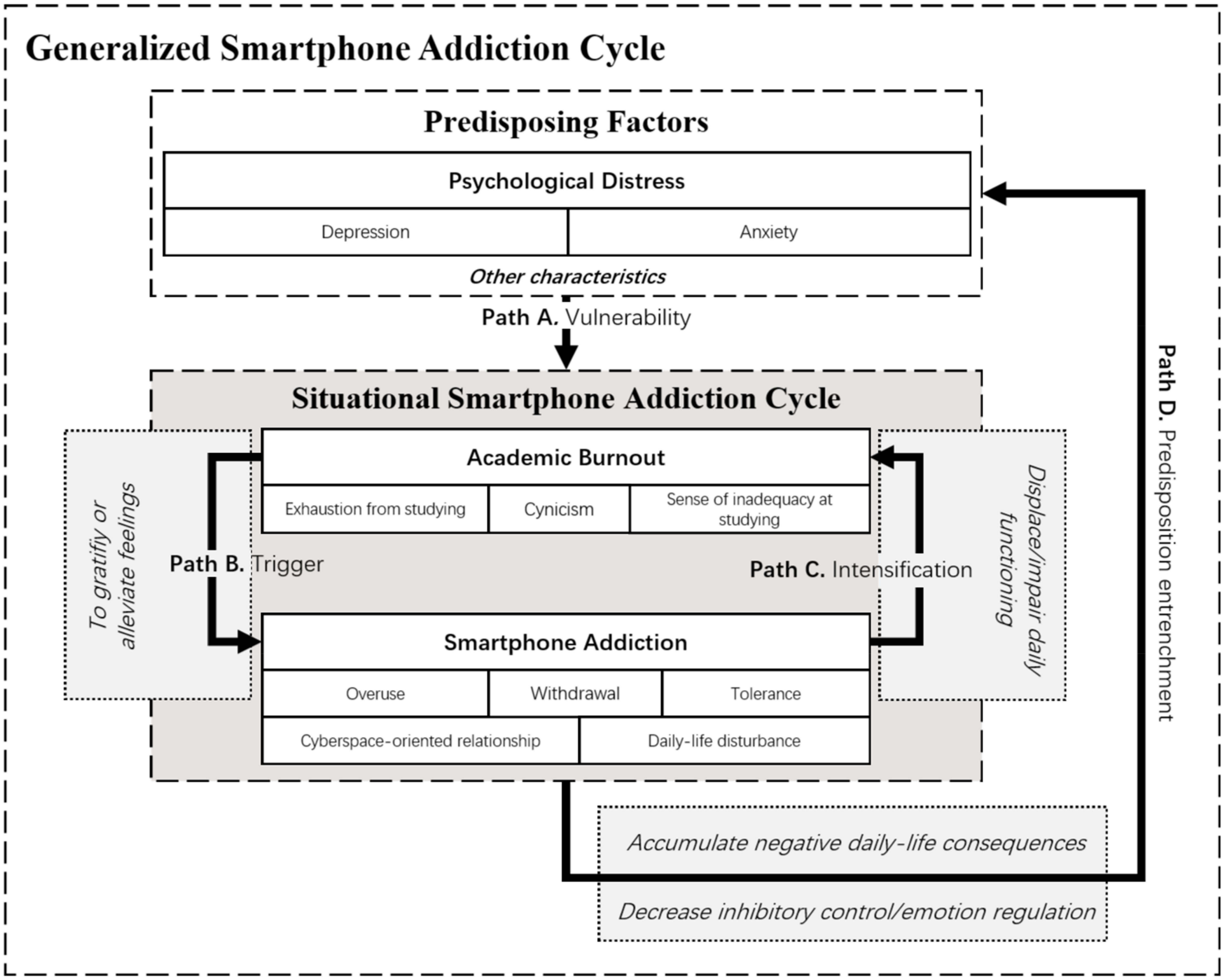

Figure 1 Generalized smartphone addiction cycle.

arousing the urge for mood modification.[45,46] To offset stress, they may increasingly resort to maladaptive smartphone use as a coping strategy, thereby reinforcing the progression toward addictive behavior patterns (see Figure 1, Path B). Adolescents who experience negative feelings due to exhaustion with schoolwork and learning inadequacy may use smartphones to offset their negative feelings. Consequently, such adolescents encountering academic burnout are likely to develop maladaptive smartphone use.

When smartphone use becomes maladaptive, the pleasurable experience derived from it gradually diminishes, and its nature shifts from pleasure-seeking to reality-avoidance. This form of escapism functionally displaces and substitutes real-world social functioning and increases an individual's vulnerability to situational difficulties (eg, academic burnout) (see Figure 1, Path C).[45,46] One symptom of smartphone addiction, overuse, directly deprives and consumes substantial time that should be devoted to social communication or studying, severely reducing effective engagement.[47] Daily-life disturbance symptoms continuously fragment attention and interrupt the learning process.[48] In the short term, adolescents with smartphone addiction are likely to develop or maintain an academic burnout state, forming a situational smartphone addiction cycle.

Then in the long term, as the addiction deepens, the diminished capacity to manage impulses and emotions resulting from uncontrolled smartphone use will expand to more fields. The accumulating negative consequences, such as chronic sleep deprivation, deteriorating real-word relationships as well as academic failure, act as persistent psychosocial stressors. Over time, this sustained stress burden, combined with the dysregulation of cognitive and emotional control,

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significantly elevates the risk for broader mental health problems.[45,49,50] Thereby transforming situational smartphone addiction cycle into more generalized smartphone addiction cycle (see Figure 1, Path D).

In general, the I-PACE model posits that, for individuals with pre-existing psychological distress, situational academic burnout may act as a trigger, leading them into a reinforcement cycle of smartphone addiction.

Longitudinal studies have adopted a cross-lagged panel modeling (CLPM) approach to examine the directional relationships between smartphone addiction and psychological distress, such as depression and anxiety, but have yielded mixed findings. For example, some studies have found a bidirectional relationship between smartphone addiction and depression.[31,32,51] By contrast, two studies identified a directional link from depression to smartphone addiction, but not in the opposite direction.[52,53] However, other studies found that smartphone addiction predicted depression, but not vice versa.[17,35,54] Regarding the relationship between smartphone addiction and anxiety, Chang et al found a bidirectional relationship.[54] However, two studies showed that anxiety predicted smartphone addiction, while the opposite direction was nonsignificant.[35,52] Overall, despite inconsistencies regarding the direction of influence, smartphone addiction is consistently associated with psychological distress.

Beyond its links to general predisposing symptoms, smartphone addiction has also been studied in relation to academic burnout. Research examining the relationship between smartphone addiction and academic burnout has used either of them to predict the other and often concluded that one can predict the other.[21,23,31,55–57] However, most such studies were cross-sectional in nature and thus were unable to determine the direction of influence.[20] Only a limited number of studies have examined the directional relationships between smartphone addiction and academic burnout. One study adopted CLPM and found that the relationship between smartphone addiction and academic burnout is bidirectional.[23] This was also supported by a study using the CLPN analysis.[34] Nonetheless, these studies were conducted at the aggregate level.

Given the connections that smartphone addiction shares with both psychological distress and academic burnout, some studies have investigated the relationship among all three factors. However, they primarily focus on investigating the potential mediation of end-to-end pathways at the overall construct level within a cross-sectional design, without addressing the possibility of reciprocal or cyclical interactions among these variables at the symptom level.[21,56–59] The directional relationships among the symptoms of these constructs remain unknown, leaving the more detailed mechanisms that underlie their coexistence unclear.

CLPN Analysis

The network theory of psychopathology proposes that mental disorders are constituted by mutually interacting symptoms.[60] These symptoms constitute a network of mental disorders, with each symptom being a node and relationships between symptoms being edges. The CLPN analysis involves combining CLPM and network analysis and is used to illustrate the temporal and directional relationships between symptoms.[44] It helps researchers to make directional inferences. A CLPN analysis of different psychological constructs at the symptom level can elucidate how different symptoms within and across constructs predict each other over time. To be more precise, it can identify the symptom that most strongly predicts the symptoms of other constructs (ie, the strongest bridging node). Furthermore, it can be used to determine the most predictive symptom within the same construct (ie, the within-construct central node). Identifying these central and bridging symptoms is crucial because it can shed light on the mechanisms underlying the comorbidity of psychological problems.[44]

A number of cross-sectional studies have conducted a network analysis of smartphone addiction and psychological distress at the symptom level.[20,61–63] Generally, these studies found that symptoms of smartphone addiction and psychological distress are correlated with each other. The central and bridging symptoms identified in these studies vary, possibly due to differences in the measurement scales used.

Some studies have adopted a CLPN approach to examine the directional relationships between symptoms of smartphone or internet addiction and psychological distress among Chinese college students. These studies found that symptoms of different constructs tended to reinforce each other over time, with symptoms of psychological distress appearing to be more predictive of smartphone or internet addiction symptoms than the reverse.[40,41] For example, Wang et al found that in the temporal network of anxiety and smartphone addiction symptoms, while symptoms from these two constructs formed a vicious cycle over time, the predictive effects of anxiety symptoms were more pronounced.[40] Similarly, Jiang et al built three temporal networks (Wave 1 to Wave 2, Wave 2 to Wave 3, and Wave 1 to Wave 3) of internet addiction and psychological distress symptoms using longitudinal data across three waves.[41] They found that symptoms of psychological distress were more predictive of internet addiction symptoms than vice versa. They also revealed that the most central and bridging symptoms differed across the three temporal networks, indicating heterogeneity in the mechanisms linking these problems over time.[41]

Furthermore, two studies conducted a CLPN analysis of smartphone addiction, psychological distress, and academic burnout among Chinese college students. One study found that academic burnout (as an aggregated variable) predicted smartphone addiction and psychological distress symptoms, while showing minimal reciprocal effects.[39] It also identified bidirectional relationships between symptoms of smartphone addiction and psychological distress, with escapism (a symptom of smartphone addiction) and social anxiety emerging as key bridging nodes.[39] However, the study did not examine how individual symptoms of academic burnout are associated with symptoms of the other two constructs. Another study conducted a CLPN analysis of smartphone addiction, academic burnout, social anxiety, and fear of missing out.[34] Nonetheless, the analysis in this case was based on the aggregate-level relationships between these constructs.

By contrast, temporal network analyses of these issues at the symptom level among Chinese adolescents appear to be limited. One study adopted a CLPN approach to examine the temporal relationships between symptoms of smartphone addiction and depression across three time points among adolescents and found that smartphone addiction and depressive symptoms reinforced each other, and that the most central symptom and bridging symptom changed over time.[42] For instance, fatigue (a depressive symptom) and daily-life disturbances (a symptom of smartphone addiction) were the most prominent bridging symptoms in the Wave 1 to Wave 2 and Wave 2 to Wave 3 networks, respectively.[42]

These studies suggest that the construction of symptom networks is a dynamic process, and that central and bridging symptoms can vary substantially across time and different groups.[42] More studies on adolescents, a group particularly vulnerable to smartphone addiction, general mental health problems, and academic burnout, are warranted to further clarify the mechanisms underlying the comorbidity of these problems.[64–66]

The key purpose of the present study was thus to fill in these research gaps by examining the directional relationships between smartphone addiction, academic burnout, and psychological distress at the symptom level using a CLPN analysis. This investigation carries significant theoretical value by moving beyond broad constructs to map the specific symptom-to-symptom pathways and temporal dynamics that underlie these common co-occurring problems in adolescents. Our findings will provide empirical evidence for unfolding the detrimental cycle among adolescents for the I-PACE model, revealing the precise reinforcement mechanism that sustains comorbidity and offering new insights into the within-construct evolution of each issue. Furthermore, the study will identify the central and predictive symptoms within the network, which can be translated directly into actionable insights for prevention and intervention. It will empower practitioners to design targeted and efficient strategies to disrupt these detrimental cycles.

Methods

Participants and Procedures

The data employed in this study originated from a research project that explored adolescents' well-being in the digital era. A two-wave survey was carried out by authors in Shenzhen, a city located in the south of China. A multistage cluster sampling design was employed, with schools recruited by the local education department based on their willingness to participate. Two high schools and six middle schools participated in the survey. We randomly selected four classes from the 10th grade in each high school, as well as two classes from the 7th grade and two classes from the 8th grade in each middle school. All students in the selected classes participated in the survey. As required by schools, students in the 9th, 11th, and 12th grades were excluded from the survey because they needed to prepare for high school or college entrance examinations.

The first-wave survey (T1) was conducted in May 2023. The second-wave survey (T2) was carried out in October 2023. We employed Wenjuanxing, an extensively used web platform for data collection in China, to collect data. Under the guidance of the third author, students completed online questionnaires in school computer rooms. At T1, 920 students completed the questionnaire. After removing all invalid questionnaires (those that did not pass the attention-check items), 810 questionnaires were left (effective response rate: 88%). At T2, 86% (787) of the students who participated in the survey in T1 were retained. Some participants were lost because they changed their classes at T2. Of the 787 participants at T2, 78% (614) remained after all invalid questionnaires had been eliminated. Therefore, we matched 614 participants from T1 to T2. Participants aged below 11 (17 cases) or above 27 (8 cases) were considered to be outliers and ultimately deleted, as Chinese adolescents in secondary schools are unlikely to be younger than 11 or older than 27. Finally, 589 participants were left for our network analysis. The participants' ages ranged between 11 and 19 (M_{age} = 15.55, SD_{age} = 1.25). Of the participants, 48.4% were male (M_{age} = 15.68, SD_{age} = 1.31), and 51.6% were female (M_{age} = 15.42, SD_{age} = 1.19).

The research design was approved by the ethical review committee at the authors' university (approval No. F089). Written informed consent was obtained from the parents or legal guardians of all participants prior to data collection. Specifically, consent forms were distributed to students to take home. Parents or legal guardians were asked to review the information and provide written consent by signing the forms. Only students who returned signed consent forms were invited to participate in the survey. Participants were first presented with an introductory page prior to accessing the online questionnaire. This page provided information about the purpose of the study, the voluntary nature of participation, the confidentiality of the data collected, and participants' right to withdraw at any time. Proceeding to the questionnaire by clicking the link on the introductory page was taken to indicate informed consent. The research team also provided a verbal explanation of these details to ensure participants' understanding. No compensation was assigned to students who undertook the survey.

Measures

Smartphone Addiction

Smartphone addiction was gauged by the short version of the Smartphone Addiction Scale (SAS).[9] This 10-item scale measures five symptoms of smartphone addiction. The first symptom was daily-life disturbances and was measured using three items (average score, T1 Cronbach's α = 0.72, T2 α = 0.81), such as "having a hard time concentrating in class, while doing assignments, or while working due to smartphone use". The second symptom is withdrawal and was measured using four items (average score, T1 α = 0.89, T2 α = 0.92), such as "feeling impatient and fretful when I am not holding my smartphone". The remaining symptoms are cyberspace-oriented relationships (measured by the item "constantly checking my smartphone so as not to miss conversations between other people on social network platforms"), overuse (measured through the item "using my smartphone longer than I had intended"), and tolerance (measured through the item "the people around me tell me that I use my smartphone too much"). Adolescents rated each item using a 6-point scale (1 = strongly disagree, 6 = strongly agree). A higher score of a symptom represents a more severe manifestation of smartphone addiction. The Cronbach's α values for the short version of SAS at T1 and T2 were 0.9 and 0.93, respectively.

Academic Burnout

Academic burnout was evaluated using the Adolescent Student Burnout Inventory (ASBI),[67] developed by Wu et al[67] based on the Maslach's academic burnout theory.[27] This 16-item scale measures three symptoms of academic burnout. The first is exhaustion from studying and was measured by four items (T1 α = 0.8, T2 α = 0.83), such as "I felt extremely tired at the end of a day's studying" and "I often feel exhausted at school". The second is cynicism toward the meaning of studying and was measured by five items (T1 α = 0.84, T2 α = 0.85), such as "I felt that study is meaningless to me" and "I hold a cynical attitude toward study". The third is a sense of inadequacy at studying, which was measured using seven items. These seven items denote positive affect (eg, "I can cope well with exams" and "I can always cope with study-related problems easily"). Thus, we reversely coded them (T1 α = 087, T2 α = 0.87). Adolescents assessed each item using a 5-point scale (1 = strongly disagree, 5 = strongly agree). For each symptom, item scores were averaged. Higher symptom scores indicate higher levels of academic burnout. Both T1 and T2 have a Cronbach's α of 0.89 for the ASBI.

Psychological Distress

In this study, two common symptoms of psychological distress were examined, namely anxiety and depression. Anxiety was measured using the Generalized Anxiety Disorder–2 scale (GAD–2).[68] The GAD–2 was found to be highly reliable and valid among the adolescent population.[69] It asks how often the respondents have experienced the following problems over the last two weeks: "feeling nervous or anxious or on edge" and "not being able to stop or control worrying". Depression was assessed by two items of the Patient Health Questionnaire–9 (PHQ–9).[70] These two items are "feeling tired or having little energy" and "feeling down, depressed, or hopeless". All of the items pertaining to anxiety and depression were rated on a four-point scale (1 = not at all, 4 = nearly every day). Average item scores were used for each symptom (anxiety: Cronbach's α at T1 = 0.84, T2 = 0.82; depression: Cronbach's α at T1 = 0.75, T2 = 0.72).

Sociodemographic Covariates

Sociodemographic characteristics, including sex, age, and the educational level of the participant's mother (coded in years of education), were controlled.

Data Analysis

Temporal Network

We used R Version 4.4.0 and RStudio Version 2023.06.1+524 to analyze the data. The basic concept of CLPN analysis is to regress each variable at Time t on all the variables at Time t – 1 simultaneously. In turn, this generates partial correlation coefficients.[44,70] These coefficients are the directed edges between nodes. Networks were estimated using nodewise LASSO regression implemented in the glmnet package in R. Specifically, each variable (symptom) at T2 was regressed on all variables at T1 while controlling for three sociodemographic covariates. LASSO regularization was applied to remove weak or spurious associations.[56] The regularization parameter (λ) was selected via 10-fold cross-validation, using the value that minimized the cross-validated prediction error. Moreover, we standardized all T1 and T2 variables except for sex to obtain standardized regression coefficients. The qgraph R package was subsequently employed to generate the temporal network from T1 to T2.

Bridging Symptoms and Within-Construct Central Symptoms

To ascertain the most predictive symptoms across and within constructs (ie, bridging symptoms and within-construct central symptoms), we calculated two centrality indices for the temporal network.[44] The first index is cross-construct out-prediction, defined as the extent to which a symptom at T1 predicts all symptoms of other constructs at T2. This was calculated by adding together the absolute values of a symptom's outgoing edges (ie, regression coefficients) to other constructs.[71] The second index is within-construct out-prediction, referring to the extent to which a symptom at T1 predicts all other symptoms of the same construct at T2 (ie, excluding autoregressive effect). This was measured by adding together the absolute values of a symptom's outgoing edges to its same construct.

Network Accuracy and Stability

In order to test the accuracy and stability of the temporal network, we used the bootnet R package to obtain a 95% confidence interval (CI) for each edge. A non-parametric bootstrap method with 1000 iterations was applied in this process.[72] We adopted the case-dropping bootstrap method and calculated the correlation stability (CS) coefficients for edges and out-prediction. The CS coefficient indicates the highest percentage of cases that can be removed with 95% confidence whilst still maintaining a correlation with the original network metric greater than 0.7.[72] While a value of CS coefficient greater than 0.5 is preferable, a value of 0.25 is acceptable.

It is worth noting that we employed dimension-level rather than item-level symptoms for two specific reasons. First, items under the same dimension were very similar. Second, the total number of items for the three constructs is 30. This results in the creation of a complex network due to the existence of too many nodes. Dimension-level symptoms can be used to obtain a parsimonious network.

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Results

Descriptive Statistics

Descriptive statistics and correlations between T1 and T2 variables are shown in Table 1 and Table 2, respectively. All symptoms of smartphone addiction, academic burnout, and psychological distress at T1 were found to be positively correlated with their symptoms at T2.

Edge Weights

Table 3 presents the edge weights (ie, the standardized regression estimates of all T1 variables on T2 variables) of the temporal network. The autoregressive edges (mean = 0.35, SD = 0.09) were higher than the cross-lagged edges (mean = 0.04, SD = 0.12), indicating that a symptom's temporal association was stronger than its temporal association with other symptoms.

Cross-Construct Analysis

Figure 2 illustrates the temporal network from T1 to T2. To facilitate interpretation, autoregressive edges, and covariates were removed from the graph.

As Figure 2 shows, the depression symptom (PD2) appeared to be the strongest bridging node. It had strong directed links to the symptoms of smartphone addiction and academic burnout, including cyberspace-oriented relationships (SA3; $\beta = 0.136$), overuse of smartphones (SA4; $\beta = 0.121$), and exhaustion from studying (AB1; $\beta = 0.144$). This is further supported by the centrality indices of cross-construct out-prediction. As presented in Figure 3, depression was found to

Table 1 Descriptive Statistics of Variables

Statistic	Mean	SD	Min	Max
Daily-life disturbances_T1	1.93	0.82	1.00	5.33
Withdrawal_T1	1.93	1.03	1.00	6.00
Cyberspace-oriented relationships_T1	2.11	1.34	1	6
Overuse_T1	2.43	1.36	1	6
Tolerance_T1	2.26	1.38	1	6
Exhaustion from studying_T1	3.22	0.84	1.00	5.00
Cynicism toward the meaning of studying_T1	2.21	0.79	1.00	5.00
Inadequacy at studying_T1	2.95	0.69	1.00	5.00
Anxiety_T1	1.99	0.75	1.00	4.00
Depression_T1	2.03	0.75	1.00	4.00
Daily-life disturbances _T2	2.08	0.92	1.00	6.00
Withdrawal_T2	2.03	1.09	1.00	6.00
Cyberspace-oriented relationships_T2	2.08	1.23	1	6
Overuse_T2	2.39	1.31	1	6
Tolerance_T2	2.20	1.26	1	6
Exhaustion from studying_T2	3.20	0.86	1.00	5.00
Cynicism toward the meaning of studying_T2	2.25	0.81	1.00	5.00
Inadequacy at studying_T2	2.88	0.67	1.00	5.00
Anxiety_T2	2.06	0.75	1.00	4.00
Depression_T2	2.12	0.78	1.00	4.00
Mother's educational level	12.44	3.33	6.00	19.00
Age	15.55	1.25	11	19
Gender	N		Percent (%)	
Male	285		48.39	
Female	304		51.61	

Note: N = 589.

Table 2 Correlations Between T1 and T2 Variables

Variables	Daily-Life Disturbances _T2	Withdrawal _T2	Cyberspace-Oriented Relationships _T2	Overuse _T2	Tolerance _T2	Exhaustion from Studying _T2	Cynicism Toward the Meaning of Studying _T2	Inadequacy at Studying _T2	Anxiety _T2	Depression _T2
Daily-life disturbances _T1	0.50***	0.45***	0.37***	0.43***	0.37***	0.23***	0.24***	0.21***	0.29***	0.28***
Withdrawal_T1	0.44***	0.57***	0.42***	0.40***	0.37***	0.28***	0.34***	0.24***	0.34***	0.32***
Cyberspace-oriented relationships_T1	0.32***	0.46***	0.47***	0.34***	0.29***	0.27***	0.21***	0.16***	0.30***	0.31***
Overuse_T1	0.33***	0.35***	0.29***	0.37***	0.32***	0.16***	0.14***	0.16***	0.15***	0.17***
Tolerance_T1	0.29***	0.34***	0.28***	0.31***	0.50***	0.21***	0.20***	0.18***	0.19***	0.23***
Exhaustion from studying_T1	0.25***	0.32***	0.28***	0.30***	0.22***	0.54***	0.34***	0.24***	0.40***	0.45***
Cynicism toward the meaning of studying_T1	0.33***	0.37***	0.30***	0.33***	0.28***	0.34***	0.59***	0.40***	0.39***	0.40***
Inadequacy at studying_T1	0.27***	0.32***	0.22***	0.30***	0.21***	0.30***	0.39***	0.66***	0.29***	0.32***
Anxiety_T1	0.35***	0.37***	0.32***	0.35***	0.25***	0.42***	0.35***	0.28***	0.59***	0.56***
Depression_T1	0.31***	0.38***	0.35***	0.36***	0.26***	0.48***	0.37***	0.31***	0.54***	0.60***
Male	−0.08	−0.07	−0.06	−0.04	0.03	−0.09*	−0.02	−0.22***	−0.13**	−0.16***
Mother's educational level	−0.09*	−0.04	−0.02	−0.05	−0.05	−0.02	−0.12**	−0.10*	−0.02	0.01
Age	0.14***	0.13**	0.09*	0.06	0.09*	0.01	0.14***	0.01	0.07	0.02

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

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Table 3 Edge Weights (Standardized Regression Coefficients) of Temporal Network from T1 to T2

Variables	Daily-Life Disturbances _T2	Withdrawal _T2	Cyberspace-Oriented Relationships _T2	Overuse _T2	Tolerance _T2	Exhaustion from Studying _T2	Cynicism Toward the Meaning of Studying _T2	Inadequacy at Studying _T2	Anxiety _T2	Depression_T2
Daily-life disturbances_T1	0.309	0.054	0.065	0.177	0.057	0.000	−0.020	0.000	0.000	0.005
Withdrawal_T1	0.137	0.345	0.090	0.090	0.083	0.063	0.165	0.000	0.110	0.080
Cyberspace-oriented relationships_T1	0.000	0.090	0.279	0.000	0.000	0.026	−0.013	0.000	0.026	0.074
Overuse_T1	0.000	0.000	0.000	0.102	0.000	−0.009	−0.074	0.000	0.000	−0.057
Tolerance_T1	0.009	0.035	0.007	0.033	0.381	0.037	0.040	0.044	0.000	0.047
Exhaustion from studying_T1	0.000	0.000	0.000	0.007	0.000	0.348	−0.048	0.000	0.000	0.040
Cynicism toward the meaning of studying_T1	0.082	0.070	0.058	0.066	0.085	0.000	0.457	0.083	0.067	0.063
Inadequacy at studying_T1	0.023	0.066	0.000	0.059	0.040	0.056	0.123	0.571	0.002	0.046
Anxiety_T1	0.143	0.069	0.031	0.063	0.021	0.052	0.021	0.000	0.369	0.191
Depression_T1	0.002	0.090	0.136	0.121	0.056	0.144	0.091	0.006	0.141	0.319

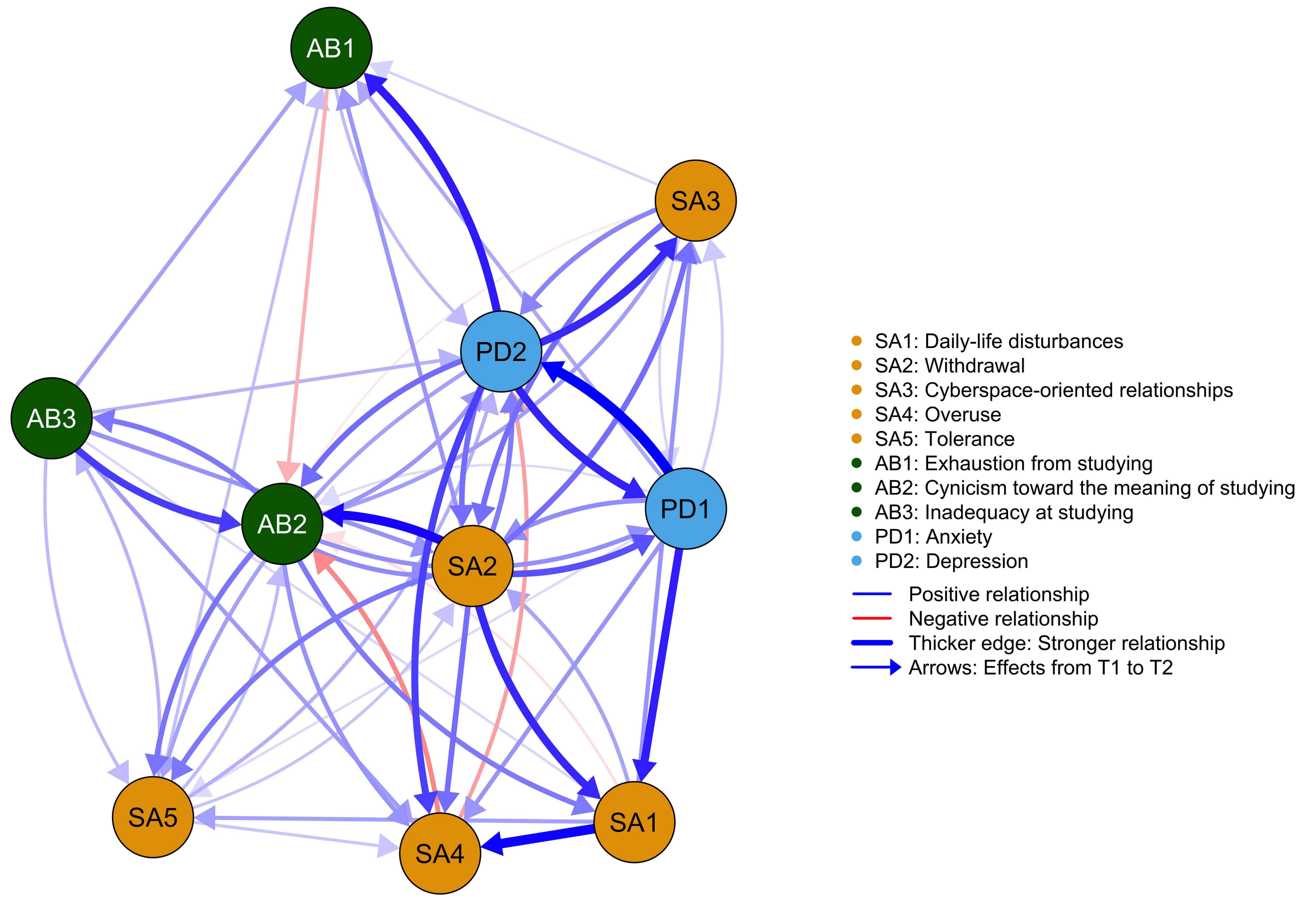

Figure 2 Temporal network of smartphone addiction, academic burnout, and psychological distress.

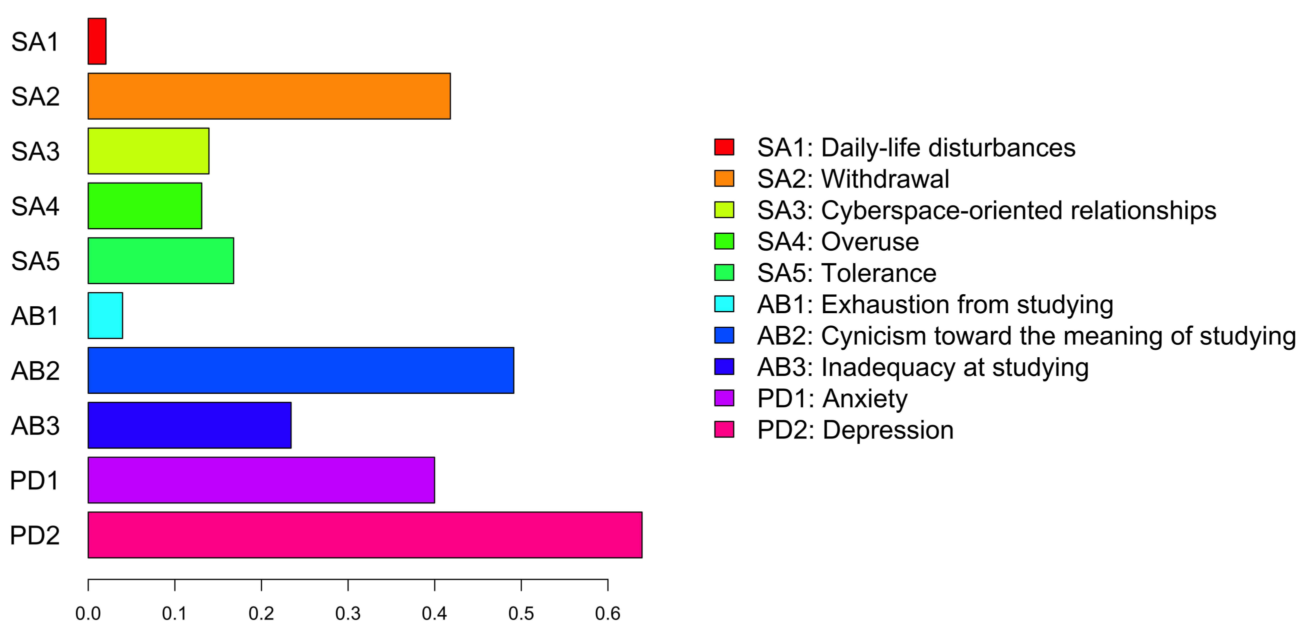

Figure 3 Cross-construct out-prediction of symptoms.

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have the highest cross-construct out-prediction value. These findings indicated that depression was a highly predictive symptom in the comorbid network.

As displayed in Figure 2, two other strong bridging nodes were identified, namely the withdrawal symptom (SA2) and the anxiety symptom (PD1). The withdrawal symptom of smartphone addiction had strong links to cynicism toward the meaning of studying (AB2; β = 0.165) and anxiety (PD1; β = 0.11). Anxiety had a strong link to daily-life disturbances (SA1; β = 0.143). By comparison, academic burnout symptoms did not have any strong directed links to smartphone addiction and psychological distress symptoms.

Within-Construct Analysis

As displayed in Figure 4, the withdrawal symptom (SA2) had the highest out-prediction value within the smartphone addiction construct, indicating that it was the most predictive node. It had a strong association with the symptom of daily-life disturbances (SA1; β = 0.137). Within the academic burnout construct, a sense of inadequacy at studying (AB3) was the most predictive node. It had a strong link to cynicism toward the meaning of studying (AB2; β = 0.123). Within the psychological distress construct, anxiety (PD1) was the central node and it was found to have a strong link to depression (PD2; β = 0.191).

Based on our cross- and within-construct analyses, several key paths linking the three constructs can be inferred. As Figure 2 shows, psychological distress primarily predicted smartphone addiction via two paths. First, depression (PD2) forecasted cyberspace-oriented relationships (SA3) and overuse of smartphones (SA4). Second, anxiety (PD1) predicted the symptom of daily-life disturbances (SA1). Third, smartphone addiction primarily predicted psychological distress via a path from the withdrawal symptom (SA2) to anxiety (PD1). Fourth, psychological distress primarily predicted academic burnout via a path from depression (PD2) to exhaustion from studying (AB1). Finally, smartphone addiction primarily predicted academic burnout via a path from the withdrawal symptom (SA2) to a cynical attitude toward studying (AB2).

As Figure 5 shows, the edges' bootstrap means basically overlapped with the estimated edges, indicating that the network is trustworthy. Moreover, the stronger the directed edge is, the less likely its bootstrapped edge CI is to contain 1, indicating that strong edges are more reliable. The CS coefficient for edges was 0.36 (95% CI 0.284 0.44), suggesting that the edge stability is acceptable. The CS coefficients for out-prediction was 0.36 (95% CI 0.284 0.44), exceeding the acceptable threshold.

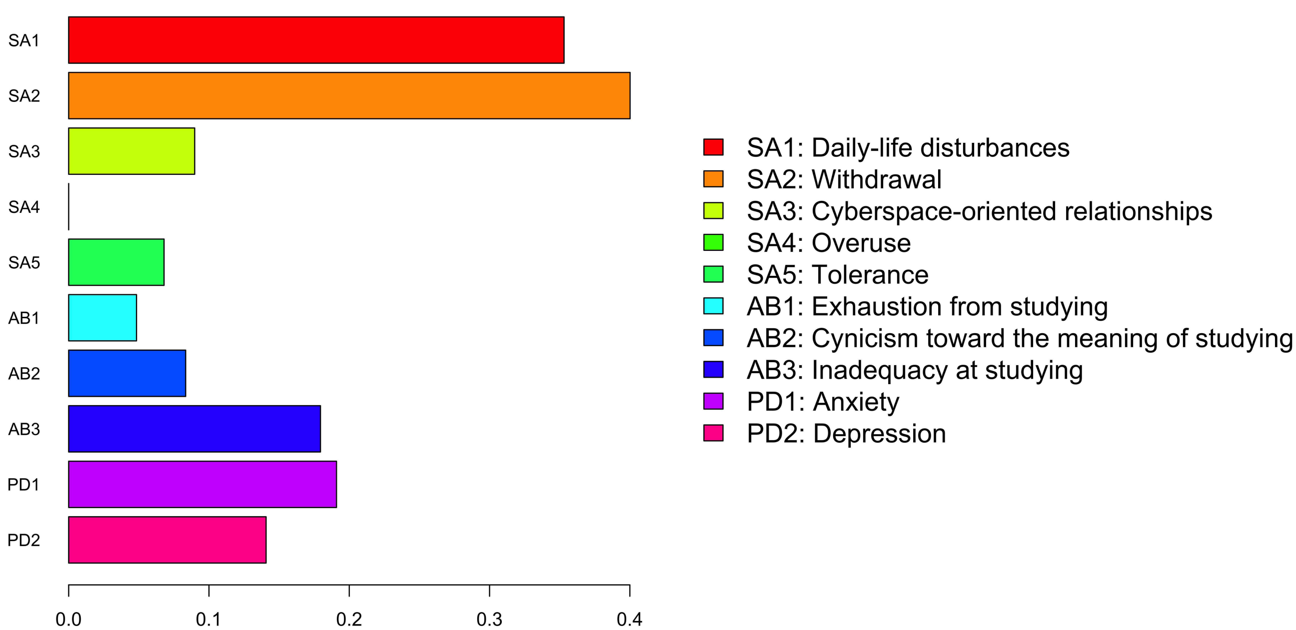

Figure 4 Within-construct out-prediction of symptoms.

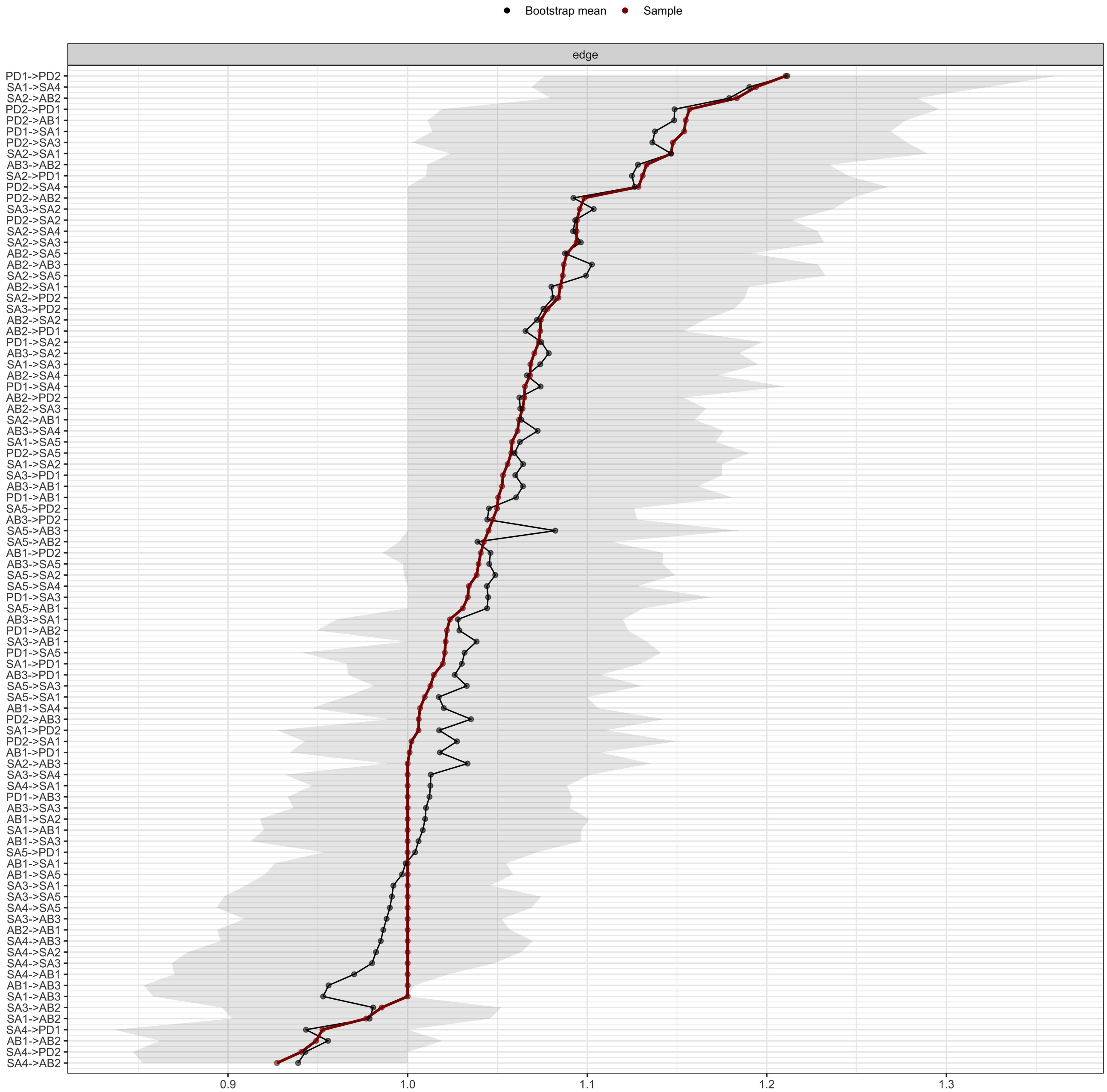

Figure 5 Bootstrapped 95% confidence intervals (the gray area) of estimated edges.

Discussion

Based on the I-PACE model, this study adopted a CLPN approach and probed the directional relationships between adolescent smartphone addiction, academic burnout, and psychological distress at the symptom level, rather than viewing these constructs as unidimensional wholes. The study identified predictive symptoms across and within constructs and elucidated important mechanisms that underlie the comorbidity of these problems.

The CLPN analysis revealed that depression was the strongest bridging symptom in the temporal network of smartphone addiction, academic burnout, and psychological distress. This finding indicated that depression may play an important role in the comorbidity of these problems. Meanwhile, two other bridging symptoms, namely the withdrawal symptom of smartphone addiction and the anxiety symptom of psychological distress, were found to have relatively strong predictive power across constructs. Within each construct, the most predictive symptoms within their respective constructs were the withdrawal symptom (from smartphone addiction), a sense of inadequacy at studying (from academic burnout), and anxiety (from psychological distress). These symptoms can predict other symptoms within their own construct, aligning with previous studies.[73–75]

Three key mechanisms underlying the comorbidity of smartphone addiction, academic burnout, and psychological distress were identified, which together construct a psychological distress-smartphone addiction cycle, with academic burnout emerging as an outcome of this cycle (see Figure 6). The first mechanism pertains to the link from psychological distress to smartphone addiction (Figure 6, Path A), specifically that depression predicted cyberspace-oriented relationships and smartphone overuse, while anxiety predicted daily-life disturbances. These results are aligned with the

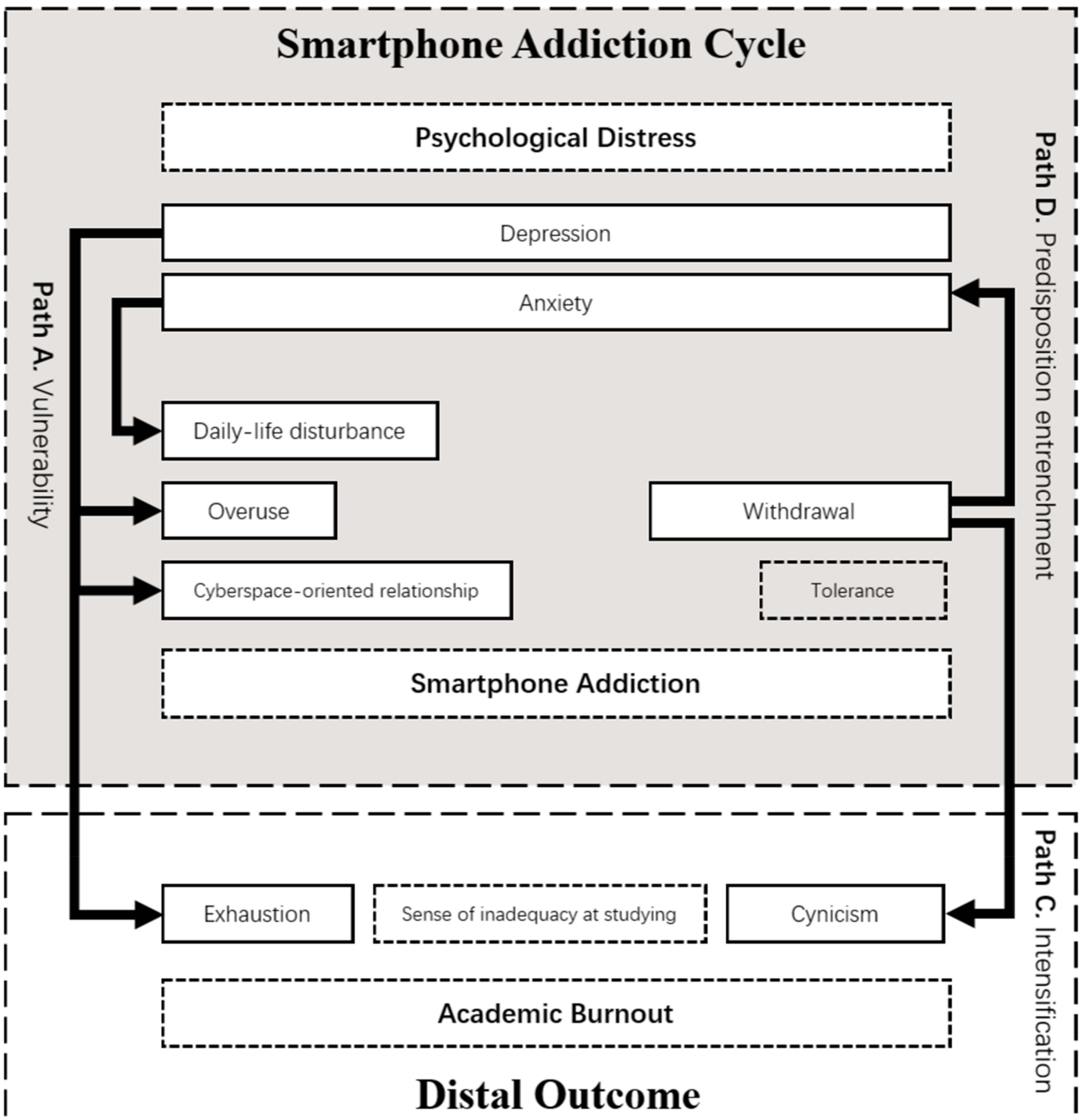

Figure 6 Generalized smartphone addiction cycle (symptom-level).

vulnerability mechanism in the I-PACE model, which posits that adolescents with psychological distress are vulnerable to addictive internet use behaviors because they tend to use the internet to offset their depressed mood and anxiety.[46,62,76,77]

The second mechanism runs from smartphone addiction to psychological distress, in that the withdrawal symptom predicted anxiety (Figure 6, Path D). This may stem from the unique characteristics that distinguish the withdrawal symptom from other symptoms. Withdrawal involves intense negative emotions in the absence of smartphone use, which inherently carries the nature of an emotional consequence of addictive behavior.[78] Thus, it has a great propensity to contribute to generalized psychological distress in nature. Furthermore, when smartphone use is discontinued, more severe withdrawal symptoms are often accompanied by heightened fear of missing out, thereby increasing individuals' anxiety.[74,79,80] Moreover, as anxiety appears to be a strong predictor of depression within the construct of psychological distress, the withdrawal symptom may also lead to depression via anxiety. These paths support the predisposition entrenchment hypothesis in the I-PACE model, which posits the long-term negative psychological consequences of addictive internet use behaviors.[45]

The third comorbidity mechanism is that academic burnout serves as a distal outcome, lying outside the vicious cycle between psychological distress and smartphone addiction. Specifically, as Figure 6 shows, depression predicted exhaustion from studying, partly due to the depletion of cognitive resources. Depression rumination persistently consumes an individual's attention and working memory,[81] leaving insufficient bandwidth for learning, thereby accelerating exhaustion from studying. Meanwhile, withdrawal predicts cynical attitudes towards studying (Figure 6, Path C), a process that can be explained by the imbalance between immediate and delayed rewards.[82] Smartphones offer instant gratification, whereas academic rewards are delayed. Withdrawal symptoms amplify the craving for immediate rewards,[83] which devalues the subjective value of delayed academic payoffs, leading to a reappraisal of studying as worthless (ie, cynicism toward studying). This path supports the intensification mechanism of the I-PACE model, which posits that addictive internet usage can substitute for social functioning and increase vulnerability to situational difficulties.[84]

These findings indicated that a bidirectional relationship exists between smartphone addiction and psychological distress at the symptom level, creating a mutually reinforcing cycle. The findings align with the theoretical relationship between psychological distress and smartphone addiction described in the adapted I-PACE framework used in this study. Specifically, it reflects the mechanism in Path A of Figure 1, where psychological distress acts as a vulnerability factor increasing the risk of smartphone addiction, and the mechanism in Path D of Figure 1, whereby such addictive behavior in turn entrenches the predisposing psychological distress. These mechanisms are consistent with existing studies using CLPN[39,40,42] or CLPM approaches.[31,32,51] However, the results contrast with those of Kang et al[52] and Zhou et al,[53] who espoused that psychological distress predicts smartphone addiction but not vice versa. They also contradict the findings of Coyne et al,[17] who were unable to identify a significant relationship between smartphone addiction and psychological distress. This discrepancy may be explained by the specific symptom-level mechanism identified in our study. For example, the relationship between anxiety and smartphone addiction was only carried by daily-life disturbance and withdrawal symptoms of smartphone addiction, but not the entire construct. Therefore, when analysis is conducted at the aggregate level, as in the studies by Coyne et al[17] and Kang et al,[52] connections between constructs may be unobserved. This highlights the importance of examining directional relationships between these constructs at the symptom level. Besides, although Jiang et al conducted a symptom-level analysis using CLPN, their assessment of internet addiction did not include the withdrawal symptom (the primary symptom predicting anxiety, as we reported).[41] This may explain why they did not reveal the directional relationship from internet addiction to psychological distress.

Furthermore, our results suggested that the predictive power that academic burnout symptoms had for smartphone addiction and psychological distress symptoms was weak in comparison to the reverse. This indicates that the situational reinforcing cycle between academic burnout and smartphone addiction proposed in the theoretical framework was not supported (Path B in Figure 1 was not identified). These results differed from those obtained by Wang et al,[23] who adopted CLPM and found that academic burnout was more predictive of smartphone addiction than the reverse. Our results also contradicted those of Salmela-Aro and Savolainen et al who found that academic burnout was more predictive of depression than the reverse.[30] Moreover, the current results are inconsistent with a CLPN study of college students, which reported that academic burnout predicted smartphone addiction and psychological distress, but not the reverse.[39] However, our results are consistent with a prior study of Chinese adolescents. That study adopted a CLPM

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approach and found that depression predicted lower academic competency, whereas the reverse association was nonsignificant.[85] A possible explanation of the weak predictive power of academic burnout symptoms in this study is that academic burnout may represent a common, and in some cases adaptive, form of disengagement from studying in Chinese adolescents, many of whom experience high academic stress.[29] This temporary form of disengagement may function as a self-protective strategy,[86] by which adolescents conserve resources and ultimately prevent academic burnout from becoming part of the psychological–smartphone addiction cycle.

Besides, the autoregressive effects of all symptoms of smartphone addiction, psychological distress, and academic burnout substantially outweighed the cross-lagged effects between them. The pattern primarily reflects the high intrinsic stability inherent to these specific symptom domains. Symptoms of addiction (eg, withdrawal) represent deeply entrenched behavioral patterns and potential neuroadaptations.[87,88] Psychological distress symptoms typically arise from persistent environmental stressors combined with stable maladaptive response tendencies.[89] Academic burnout symptoms are often grounded in chronic exposure to demanding educational environments and resource depletion.[90,91] Consequently, each symptom demonstrates a strong tendency for self-perpetuation over the observed interval. While cross-lagged effect sizes were smaller relative to the autoregressive effects, these paths provide essential evidence for specific directional predictions and potential mechanisms linking distinct constructs. They illuminate the dynamic interplay that contributes to the co-occurrence and mutual reinforcement of these conditions, offering vital insight for theoretical models and identifying intervention implications.

Limitations and Future Research Directions

This study has some limitations. The first limitation relates to the measures used in this study. The smartphone addiction symptoms were assessed using the short version of SAS. To better detect smartphone addiction symptoms, future studies should consider using the long version. The second limitation concerns the analysis at the dimension level rather than the item level. While this approach preserved model parsimony and avoided overfitting in our 10-node cross-lagged network,[72] it may obscure nuanced within-dimension dynamics. Future studies should employ multilevel network models to reconcile dimension-level with item-level.[92] The third limitation was that we only had access to two-wave data. Future research should consider using data with more waves in order to better clarify the longitudinal relationships between these constructs. The fourth limitation was that the broad age range of our sample, which was chosen to capture generalized adolescent patterns, may obscure developmental differences. The manifestations of longitudinal networks are likely to vary between early, middle, and late adolescence. Our analytical approach, which treated age as a covariate, was designed to test the overarching relationship but cannot delineate these potential stage-specific dynamics. Future work with large samples at each developmental stage is needed to directly compare these relationships across adolescence and to uncover potential developmental differences. The final limitation was related to the shortcomings of cross-lagged models, such as time lag, measurement error, and the inability to differentiate between within- and between-persons variances.[44] These shortcomings render cross-lagged models unable to determine causality. In this regard, researchers suggested that CLPN results should be interpreted in the sense of prediction rather than causation.[44] Future research should combine multilevel models and network analysis to determine the directional relationships between symptoms.[43,93]

Practical Implications

This study has significant practical implications for intervening in the comorbidity of smartphone addiction, academic burnout, and psychological distress, as well as the occurrence of each single problem among Chinese adolescents. First, given that both depression and anxiety emerged as strong bridging symptoms in the temporal network, interventions should prioritize addressing psychological distress symptoms to prevent the concurrence of the three problems. To achieve this, routine school-based screening utilizing validated instruments should be implemented to facilitate the early identification of at-risk students. Recent developments in artificial intelligence–assisted mental illness risk screening tools can not only improve the speed and timeliness of identifying at-risk individuals but also enhance screening accuracy and coverage.[94] Schools can adopt these tools to routinely screen for at-risk students while respecting students' autonomy in participation and safeguarding their privacy. Moreover, integrating emotion regulation skill development into regular curricula can enhance students' distress tolerance. Furthermore, given that psychological distress predicted smartphone addiction via the path from depression to smartphone overuse and cyberspace-oriented relationships, as well as the path from anxiety to daily-life disturbances, tailored intervention strategies may be designed to disrupt these pathways. For example, providing more rewarding face-to-face activities (eg, peer group activities, sports, or school clubs) for adolescents with depressive or anxiety symptoms may help reduce their reliance on smartphones as a means of alleviating negative emotions.[95]

Second, as the withdrawal symptom was an important bridging node and a central node within the smartphone addiction construct, intervention schemes can focus on it in order to reduce the risk of smartphone addiction and the comorbid problems. The symptom of withdrawal comprises a set of negative feelings, such as anxiety and irritability, when not holding the device. Therefore, emotion regulation training, such as mindfulness-based strategies, is recommended to address these negative feelings.[96] Moreover, according to the literature, fear of missing out is a key driver of withdrawal-linked anxiety.[79] Therefore, cognitive reappraisal of the value of keeping up with online updates, as well as planned digital engagement instead of continuous checking, are recommended to address this anxiety driver. Other common strategies, such as the gradual reduction of smartphone use and the reduction of cues that trigger craving (eg, turn off non-essential notifications and keep the device out of immediate reach),[97,98] are also recommended.

Third, as the sense of inadequacy at studying was the central node within the academic burnout construct, interventions can draw on this to prevent academic burnout. As existing research confirms that adolescents' sense of inadequacy at studying is related to high study demands and academic stress,[26,29] practical intervention efforts should focus concurrently on reducing environmental pressures and building student competence. This requires system-level action by education practitioners to review and reduce excessive loads and high-stakes testing critically. Concurrently, engaging parents through workshops to cultivate realistic expectations and supportive home learning environments is crucial. Furthermore, the finding that the withdrawal symptom was linked to cynicism toward studying suggests that adolescents tend to seek immediate gratification from smartphone use while discounting the value of academic payoffs, which require long-term effort.[82,83] Interventions should target adolescents with withdrawal symptoms and provide more immediate positive feedback on their studies, thereby helping them regain interest in learning.

Fourth, the finding that autoregressive effects outweighed cross-lagged effects across all constructs suggests that early intervention is crucial. Maladaptive symptoms tend to be stable over time once established. Hence, interventions should begin in early adolescence. Schools and families should collaborate to promote adolescents' healthy digital habits and psychological resilience, enabling them to better regulate smartphone use and cope with psychological distress and academic stress.

Overall, the results underscore the importance of targeting symptom-level links to disrupt the smartphone addiction cycle. Traditional approaches that focus on unified constructs may overlook critical mechanisms that are key to addressing co-occurring problems.

Conclusion

In conclusion, based on the I-PACE model, this study provides not only longitudinal evidence for the I-PACE theoretical framework but also detailed insights into the mechanisms linking constructs within the model through temporal and symptom-level network analysis. This study highlights the critical role of predisposing factors (ie, psychological distress symptoms) in the smartphone addiction cycle depicted by the I-PACE model. However, the results suggest that school situational factors such as academic burnout may function as distal outcomes rather than triggers in this cycle among Chinese adolescents. Future research may develop hypotheses regarding the relationships between predisposing and school situational factors and other internet addiction behaviors based on the I-PACE model and the mechanisms identified in this study. Practically, this study underscores the importance of prioritizing interventions targeting psychological distress symptoms to disrupt the smartphone addiction cycle.

Data Sharing Statement

The data used in this study are available from the corresponding author upon reasonable request.

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Ethical Approval

This study was performed in line with the principles of the Declaration of Helsinki. The Human Research Ethics Committee of Tsinghua University approved this research [No. F089].

Informed Consent

Informed consent was obtained from all the participants and their legal guardians.

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Disclosure

The authors report no conflicts of interest in this work.

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