Adolescents Lost in the 'Net': Symptom Evolution in Youth at Risk for Internet Addiction

Authors: Chen Shiyun, Qu Diyang, Bu He, Liang Kaixin, Zhang Peichao, Chi Xinli, Xinli Chi

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Abstract

This study conducted three-year longitudinal measurements on 1,279 first-year junior high school students in Shenzhen, employing growth mixture model and network analysis methods to identify adolescents at risk for internet addiction and the evolution patterns of their internet addiction symptoms. Growth mixture model results showed that adolescents could be distinguished into normal and risk groups based on developmental trends of internet addiction. Network analysis results indicated that internet addiction among risk group adolescents presented different core symptoms across stages: in the first year of junior high school, compulsive internet use, loss of satisfaction, emotional dyscontrol, and withdrawal symptoms all had relatively high centrality; in the second year, loss of satisfaction became the core symptom with the highest centrality at that time point; in the third year, withdrawal symptoms became the core symptom with the highest centrality. This study broadens understanding of the dynamic variability of adolescent internet addiction, expands methods for identifying adolescents at risk for internet addiction, and provides empirical evidence for designing targeted intervention programs in the future.

Full Text

Lost in the "Net": Symptom Evolution of Adolescents at Risk for Internet Addiction

CHEN Shiyun[1,2], **QU Diyang**[3], **BU He**[4], **LIANG Kaixin**[1], **ZHANG Peichao**[5], **CHI Xinli**[1]

[1] School of Psychology, Shenzhen University, Shenzhen, Guangdong 518061, China
[2] Department of Applied Social Sciences, The Hong Kong Polytechnic University, Hong Kong SAR, China

[3] Vanke School of Public Health, Tsinghua University, Beijing 100091, China
[4] School of Social and Public Administration, East China University of Science and Technology, Shanghai 200237, China
[5] Research Center for Modern Psychology, Wuhan University, Wuhan, Hubei 430072, China

Abstract

This study conducted a three-year longitudinal assessment of 1,279 seventh-grade students in Shenzhen, employing growth mixture modeling and network analysis to identify adolescents at risk for internet addiction and examine the evolution of their addiction symptoms. Growth mixture model results revealed that adolescents could be distinguished into normal and risk groups based on their developmental trajectories of internet addiction. Network analysis indicated that core symptoms of internet addiction among the risk group varied across different stages: in seventh grade, "Compulsive Internet Use," "Lack of Satisfaction," "Emotional Dyscontrol," and "Withdrawal Symptoms" all exhibited high centrality; in eighth grade, "Lack of Satisfaction" became the most central symptom; and in ninth grade, "Withdrawal Symptoms" emerged as the most central symptom. These findings broaden our understanding of the dynamic nature of adolescent internet addiction, expand methods for identifying at-risk adolescents, and provide empirical evidence for designing targeted intervention programs.

Keywords: Internet addiction, network analysis, developmental trajectory, longitudinal study, symptom evolution

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Introduction

In modern society, the internet has become an indispensable part of daily life, with adolescents representing one of its primary user groups. According to the *China Statistical Report on Internet Development* (2022), adolescents accounted for 13.5% of all internet users in China as of June 2022 (CNNIC, 2022). While appropriate internet use can benefit adolescents by facilitating information exchange and building social support networks, excessive dependence may lead to numerous negative consequences, including internet addiction (hereafter "internet addiction"; Chi et al., 2020; Pan et al., 2020). Internet addiction refers to individuals' excessive dependence on internet use without the influence of other addictive substances, resulting in impairments to academic performance, interpersonal relationships, and social functioning (Young, 1998). Due to adolescents' immature psychological and physical development, limited ability to discern the quality of online information (Kuss et al., 2013), and insufficient self-regulation regarding internet use (Tokunaga, 2015), this population constitutes a high-risk group for internet addiction. According to the China Internet Network Information Center, the detection rate of internet addiction among Chinese adolescents has reached 19.5% (CNNIC, 2022), meaning nearly 33.15 million adolescents in China exhibit internet addiction. Extensive research has demonstrated that internet addiction adversely affects adolescents' physical health (Güzel et al., 2018), academic performance (Kuss et al., 2014), and mental health (Singh & Barmola, 2016). Given the high prevalence and harmful consequences of adolescent internet addiction, there is an urgent need to broaden and deepen our understanding of this phenomenon to provide new perspectives and solutions for assessment and early warning.

Adolescence is a period of dramatic physical and psychological changes. Previous research suggests that identifying and assessing adolescents at risk for internet addiction requires consideration of its dynamic nature (Bu et al., 2021). For example, Chang et al. (2014) tracked 2,315 Taiwanese high school students in 10th grade and found that one-sixth developed internet addiction one year later (in 11th grade), while one-seventh showed significantly reduced addiction levels. Subsequent studies across different regions of China have similarly validated the dynamic changes in adolescent internet addiction across different stages. For instance, Bu et al. (2021) found in a longitudinal study of Shenzhen adolescents that among those exhibiting internet addiction in seventh grade, 59.3% saw their addiction levels drop below the clinical threshold over time, while 10.2% of those without addiction in seventh grade developed it by eighth grade. However, these studies used only two waves of data, which cannot reveal developmental trends and critical inflection points. Moreover, relying solely on threshold criteria to distinguish between "with" and "without" internet addiction categories and defining developmental patterns based on category changes across time points may overlook heterogeneity in addiction trajectories—that is, adolescents with the same category changes may exhibit completely different developmental patterns. For example, based on threshold criteria, adolescents classified as non-addicted at both time points are often considered risk-free, yet this group may actually be on a trajectory toward risk. Therefore, incorporating considerations of heterogeneity in internet addiction trajectories can provide a more comprehensive and clearer picture of adolescent internet addiction development beyond threshold-based identification of at-risk groups.

Research has shown that using Growth Mixture Models (GMM) to examine internet addiction trajectories can effectively address these limitations (Choo et al., 2021). Previous studies have confirmed the unique advantages of GMM in identifying at-risk groups for internet addiction. For example, Choo et al. (2021) identified three heterogeneous groups among adolescents defined as addicted at one or more time points based on threshold criteria: a borderline group (meeting the threshold at the first time point with subsequent levels fluctuating near the threshold), an improvement group (far exceeding the threshold at the first time point with subsequent levels fluctuating near the threshold), and a fluctuating group (far exceeding the threshold at two non-consecutive time points while remaining below the threshold at the other three time points). Additionally, scholars such as Hong et al. (2014) and Zhou et al. (2018) examined internet addiction trajectories among Korean adolescents and Chinese adolescents who experienced traumatic events, respectively, and similarly found group differences among those showing high addiction levels at one or more time points, including both groups with gradually increasing addiction and groups with slowly decreasing high-level addiction. Thus, compared to threshold-based approaches, trajectory-based identification of at-risk adolescents is superior. Furthermore, according to the "failure compensation" hypothesis, internet use represents a compensatory behavior when adolescents encounter obstacles in psychological development. In this process, if adolescents adopt "constructive compensation"—such as using social networking platforms to improve peer relationships or moderately playing online games to relieve pressure to meet needs arising from developmental obstacles—they can successfully complete compensation and return to normal internet use levels from temporary excessive use, representing normal internet behavior. However, if they adopt "pathological compensation," such as using the internet to escape real-life problems or making it the sole source of satisfaction and support, failure compensation occurs, leading to developmental deviation or interruption and resulting in internet addiction behavior (Gao & Chen, 2006). This theory suggests that based on different compensation methods, heterogeneous groups may exist in adolescent internet addiction trajectories. Therefore, this study first employs GMM analysis with three waves of longitudinal data across three years to identify heterogeneous groups in adolescent internet addiction trajectories and proposes the following hypothesis: Adolescent internet addiction trajectories exhibit group heterogeneity, with a risk group showing increasing internet use behaviors that eventually develop into internet addiction (Hypothesis 1).

For adolescents in the risk group showing problematic developmental trends, this study further examines their symptom presentation. Since internet addiction has not been defined as a mental disorder by the World Health Organization (WHO), the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV), or the International Classification of Diseases (ICD-10), its definition and symptom identification remain controversial in academia. It is widely accepted that internet addiction is a type of addictive behavior, and its symptoms are identified by referencing criteria for other addictive behaviors. Among these, the eight symptoms proposed by Young (1998) are most widely applied as criteria for identifying internet addiction: (1) compulsive internet use; (2) guarantee of satisfaction; (3) repeated unsuccessful attempts to reduce internet use; (4) irritability, depression, or emotional instability when internet use is restricted; (5) excessive time consumption; (6) jeopardizing work or social relationships for internet use; (7) concealing internet use behavior; and (8) escaping reality. Based on these eight criteria, scholars have developed internet addiction scales with 7 items (Griffiths, 1998), 8 items (Suler, 2004), 10 items (Young, 1998), and 20 items (Young, 1998). However, the original 7-item and 9-item scales were not developed specifically for internet addiction behaviors but rather by referencing criteria for gambling addiction and psychoactive substance dependence in the DSM-IV, and thus have been used less frequently in subsequent research (Griffiths, 1998; Suler, 2004). Subsequently, Shek et al. (2008) confirmed that

Young's 10-item Internet Addiction Test (IAT-10) demonstrated good reliability and validity among Hong Kong adolescents by comparing it with the Chinese version of the Goldberg Internet Addiction Scale. The 10-item scale, based on Young's (1998) eight symptoms, subdivides the "repeated attempts to reduce internet use" symptom into "withdrawal symptoms" and "emotional dyscontrol symptoms." Withdrawal symptoms focus on negative emotional reactions after stopping internet use, while emotional dyscontrol symptoms focus on negative emotional reactions when attempting to control or reduce internet use. Additionally, because excessive financial costs caused by internet addiction are considered a prominent symptom (Cao & Su, 2007), the 10-item scale includes a new symptom focusing on internet-related expenses, incorporating excessive financial consumption as a criterion for internet addiction. Based on this, this study uses the Chinese version of the 10-item Internet Addiction Test validated by Shek et al. (2008) (Young, 1999), treating individual items as different symptoms of internet addiction to examine their developmental evolution (Hirota et al., 2020). In recent years, the development of psychopathological network theory has provided new perspectives for examining the causes and high relapse rates of adolescent internet addiction. According to this theory, one or several highly central symptoms exist in the internet addiction symptom network (called core symptoms) that activate other symptoms, forming a negative cycle that leads to the continuous development of addictive behavior (Borsboom & Cramer, 2013; Borsboom, 2017). Moreover, higher global network strength indicates tighter internal connections among symptoms, greater stability, and stronger vulnerability to internet addiction (Borsboom, 2017; Tio et al., 2016). Compared to previous research, psychopathology-based network analysis can more intuitively demonstrate the roles played by different symptoms and their interconnections in internet addiction, thereby providing empirical evidence for identifying and intervening with core symptoms among at-risk adolescents.

Currently, only two studies have used network analysis to examine adolescent internet addiction, with consistent results indicating that different internet addiction symptoms and their pairwise associations play unique roles in the network. For example, Hirota et al. (2020) conducted a symptom network analysis of Japanese adolescent internet addiction and found that "internet use affecting learning efficiency" was the core symptom with the greatest influence on other symptoms. Additionally, Liu et al. (2022) analyzed internet addiction symptom networks among Chinese adolescents at different pubertal stages and found that the core symptom was "lack of satisfaction" in early puberty, "reduced sleep," "inability to stop internet use," and "feeling depressed" in mid-puberty, and "feeling depressed" in late puberty. However, since existing network analysis studies on adolescent internet addiction have used cross-sectional designs, how internet addiction symptoms evolve over time remains unknown. Although Liu et al. (2022) examined changes in core symptoms across different pubertal stages, their study compared symptom networks across three independent samples, making results vulnerable to individual differences between samples. Therefore, it is necessary to use longitudinal designs to examine symptom network evolution in the same cohort. Scholars have proposed that both network comparison analysis and between-subject network analysis (e.g., cross-lagged network analysis) are suitable for longitudinal data (Robinaugh et al., 2020), though their foci differ. The former emphasizes differences in core symptoms and symptom associations across time points, while the latter focuses on revealing causal relationships across time. Current academic consensus holds that both methods provide valuable partial information, though debate continues regarding which better captures relationships among psychiatric symptoms (Robinaugh et al., 2020). Based on our research purpose, we employed network comparison analysis to explore symptom network evolution among adolescents in the internet addiction risk group, aiming to answer the following research questions: How do the overall connectivity of internet addiction symptoms and pairwise symptom associations differ across time points, and do core symptoms of internet addiction change across different time points?

In summary, this study selected adolescents in seventh grade as participants, employed a three-wave longitudinal design over three years, and combined GMM and network analysis to identify adolescents at risk for internet addiction and examine their symptom evolution patterns. The study aims to achieve the following objectives: (1) Distinguish different heterogeneous groups based on adolescent internet addiction trajectories and hypothesize the existence of an internet addiction risk group; (2) Compare internet addiction symptom networks of the risk group across different time points at the symptom level (overall symptom connectivity and pairwise symptom associations) and identify core symptoms at different stages.

Method

2.1 Participants and Procedure This study employed cluster random sampling, with schools as the sampling unit. Five middle schools in Shenzhen were randomly selected using a random number table. Participants from each school were 2016 cohort seventh-grade students who completed three annual assessments at one-year intervals. This research project was part of the Shenzhen Adolescent Mental Health Survey, which used a large-sample longitudinal design to explore developmental characteristics and mechanisms of positive youth development, internet addiction, depression, and internalizing/externalizing behaviors, aiming to reveal developmental changes and individual differences in adolescent psychosocial development and promote healthy adolescent growth. The assessments were administered by graduate students in psychology who received unified professional training from the project leader on test purposes, content, requirements, procedures, and precautions. Before assessment, school and homeroom teacher consent was obtained, and parents and students were informed about the overall testing situation with parental consent and student assent secured. During assessment, paper-and-pencil questionnaires were administered uniformly in classrooms by class unit, with questionnaires collected immediately upon completion. The same procedure was used at all three time points.

Data were first collected from October to November 2016 (T1), with follow-up surveys conducted annually. The second assessment (T2: October to November 2017) yielded 1,511 valid participants, and the third assessment (T3: October to November 2018) yielded 1,480 valid participants. Since existing network analysis methods cannot handle missing data (Epskamp & Fried, 2018), participants who did not report gender and age or did not complete all internet addiction items were excluded. Differential tests showed no significant differences between retained and excluded participants in gender ($p = 0.15$), age ($p = 0.66$), or T1 internet addiction scores ($p = 0.79$), indicating no systematic attrition. The final sample consisted of 1,279 participants who completed questionnaires at all three time points, including 662 boys (51.8%) and 617 girls (48.2%). The mean age at initial assessment was 12.46 years (SD = 0.63). Harman's single-factor test was used to test for common method bias, revealing seven factors with eigenvalues greater than 1, with the largest factor explaining 17.55% of variance, far below the 40% critical threshold, suggesting no significant common method bias in this study.

2.2 Measures **10-Item Internet Addiction Test (IAT-10).** Young's (1999) 10-item Internet Addiction Test was used at all three time points. Shek et al. (2008) confirmed that the Chinese version of this scale demonstrates good reliability and validity among Chinese adolescents. The scale comprises 10 internet addiction symptoms, with participants responding "yes" (scored 1) or "no" (scored 0) based on their internet use over the past year, for a total of 10 items. Previous research recommends using 4 as the cutoff score, with individuals scoring 4 or above considered to have internet addiction (Shek et al., 2008). In this study, Cronbach's alpha coefficients at the three time points were 0.76, 0.75, and 0.83, respectively. The scale also demonstrated good structural validity at all three time points ($^2 = 185.31$–245.05, df = 34, $p < 0.001$, CFI = 0.91–0.93, TLI = 0.88–0.91, RMSEA = 0.06–0.09, SRMR = 0.04).

2.3 Statistical Analysis This study first used Mplus 8.0 (Muthén & Muthén, 2017) for descriptive statistics and correlation analysis. Second, gender and age were included as covariates in GMM to estimate developmental trajectories of different heterogeneous groups and differential tests were used to compare demographic differences between groups. Finally, R-package version 4.1.3 was used to estimate network structures and central symptoms of the internet addiction risk group at three time points.

2.3.1 GMM Analysis Based on three waves of longitudinal data, we first evaluated and compared GMM fit to analyze heterogeneity in three-year developmental trajectories of adolescent internet addiction. Traditional growth models assume all individuals in a sample share the same growth trajectory, whereas GMM allows for within-group heterogeneity by assuming different subgroups in the sample have similar but not identical growth trajectories. GMM's unique advantage lies in its ability to more accurately identify risk groups for internet addiction by considering individual differences in developmental trajectories while accounting for time factors. This study employed GMM with freely estimated growth factor variances and covariances, allowing all individuals within a class to have non-identical growth trajectories to maximize optimization of fit and reflect trajectory heterogeneity. In GMM analysis, both intercept and slope have mean and variance parameters. The intercept mean describes the average initial level, while intercept variance reflects the degree of individual differences at a specific time point, with larger variance values indicating more pronounced initial level differences between individuals. The slope mean represents the average growth rate across time points, while slope variance reflects individual differences in growth rates, with larger variance values indicating more pronounced differences in developmental trajectories between individuals (Wang et al., 2017). GMM model fit indices include information criteria: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (aBIC), and Entropy; and test statistics: Lo-Mendell-Rubin likelihood ratio test (LMR) and Bootstrapped Likelihood Ratio Test (BLRT). According to the selection criterion that "higher Entropy and lower AIC, BIC, and aBIC indicate better model fit, with LMR and BLRT p-values reaching significance," and ensuring each class comprises at least 5% of the sample, the optimal class model was determined (Zhang et al., 2010).

2.3.2 Network Analysis R-package was used to estimate internet addiction symptom networks at different time points, following the standard guidelines published by Epskamp and Fried (2018).

First, the R package IsingFit was used to estimate and visualize symptom networks. The eLasso method based on the Ising model was employed, using regularized logistic regression to estimate network structure. To avoid false positive associations, the Graphical Least Absolute Shrinkage and Selection Operator (GLASSO; Tibshirani, 1996) was used for control. This method is suitable for estimating weighted undirected networks from binary data, where network edges can be understood as weighted averages of regression equation coefficients (slopes and intercepts) of one variable regressed on all others. Since the networks in this study had relatively few nodes, the OR rule was used to define the existence of nodes and edges for greater sensitivity—that is, if one of two regression coefficients was non-zero, an edge was defined as present (Van Borkulo et al., 2014). To include covariates affecting the network (gender and mean internet addiction scores), the method recommended by Funkhouser (2020) was used, incorporating covariates into network estimation without discussing their effects on individual internet addiction symptoms. Second, the R package Network Comparison Test (NCT) was used to compare network structure, strength centrality, and edge connectivity differences across the three time points through 1,000 iterations of permutation testing (Van Borkulo et al., 2022), with significance set at 0.05. Third, centrality indices were used to evaluate the role of each symptom in the network. Common centrality indices include strength centrality, betweenness, and closeness (Opsahl et al., 2010). Since previous research has shown that strength centrality has higher stability, this study primarily interpreted this index, with the other two as references (Liang et al., 2020). In this study, all centrality coefficients were standardized Z-scores, with higher coefficients indicating that a symptom was more likely to activate other symptoms in the network, thereby identifying the most important symptoms at each time point. Finally, the R package bootnet was used to analyze the accuracy of network estimation, edge estimation, and centrality estimation. Edge accuracy was estimated through 95% confidence intervals of bootstrapped edge weights, with smaller confidence interval coverage indicating more accurate edge estimation. Centrality stability was assessed through subset bootstrap procedures that removed a certain proportion of participants and re-estimated node centrality; the proportion removed when the correlation between this centrality and the original centrality index reached 0.7 was defined as the centrality stability coefficient (CS-coefficient). CS-coefficients greater than 0.25 indicate acceptable stability, while those greater than 0.50 indicate good stability.

Results

3.1 Descriptive Statistics and Correlation Analysis Total scores across all items were used to measure adolescent internet addiction severity (item response rates are shown in Table 1). Table 2 presents means, standard deviations, and correlation analyses for all participants across three time points. Results showed that mean internet addiction scores were highest at T2, followed by T1, and lowest at T3. The prevalence of internet addiction was 14.1% in seventh grade, rising to 15.6% in eighth grade, then declining to 14.9% in ninth grade. Additionally, standard deviations increased annually across the three time points, indicating increasing individual differences in internet addiction scores and suggesting substantial heterogeneity among adolescents. Correlation analyses revealed that the correlation coefficient between seventh and eighth grade internet addiction scores was 0.25 ($p < 0.01$), between eighth and ninth grade was 0.24 ($p < 0.01$), and between seventh and ninth grade was 0.38 ($p < 0.01$). According to criteria for relative stability coefficients, internet addiction scores showed low stability across adjacent time intervals and moderate stability across the two-year interval.

Table 1 Response Rates for Internet Addiction Items Across Three Time Points (N = 1279)

Item	T1 (%)	T2 (%)	T3 (%)
1. Do you feel preoccupied with the internet?			
2. Do you feel the need to use the internet with increasing amounts of time to achieve satisfaction?			
3. Have you made repeated unsuccessful efforts to control, cut back, or stop internet use?			
4. Do you feel restless, moody, depressed, or irritable when attempting to cut down or stop internet use?			
5. Do you stay online longer than originally intended?			

Item	T1 (%)	T2 (%)	T3 (%)
6. Have you jeopardized or risked the loss of a significant relationship, job, educational, or career opportunity because of the internet?			
7. Have you lied to family members, a therapist, or others to conceal the extent of your internet use?			
8. Do you use the internet as a way of escaping from problems or relieving dysphoric mood (e.g., feelings of helplessness, guilt, anxiety, depression)?			
9. Do you feel depressed, restless, moody, or anxious when not online?			

Item	T1 (%)	T2 (%)	T3 (%)
10. Do you continue to use the internet despite having spent excessive money?			

Note: T1 = First assessment, T2 = Second assessment, T3 = Third assessment.

Table 2 Descriptive Statistics and Correlation Analysis of Internet Addiction Scores Across Time Points (N = 1279)

Variable	M	SD	1	2	3
1. T1 Internet Addiction			1		
2. T2 Internet Addiction			0.25***	1	
3. T3 Internet Addiction			0.38***	0.24***	1

Note: **p < 0.001. M = Mean; SD = Standard deviation. T1 = First assessment, T2 = Second assessment, T3 = Third assessment.*

3.2 GMM Analysis GMM models with 1 to 5 classes were fitted, with fit indices shown in Table 3 . Across all models, the BLRT and LMR for the four-class model did not reach significance, suggesting that two- and three-class models were preferable. Considering that the two-class model had higher Entropy, indicating more accurate classification, the two-class model was selected after comprehensive consideration. We further examined the developmental trajectory characteristics of the two latent classes. Results showed that the intercept means for the two latent classes were C1: 2.36 (SE = 0.25, t = 9.47, $p < 0.001$) and C2: 1.48 (SE = 0.05, t = 27.32, $p < 0.001$). The intercept means differed significantly between the two classes, with C1 showing higher initial internet addiction scores and C2 showing relatively lower initial scores. Additionally, slope means were examined to assess average growth rates for each class. The slope means for the two latent classes were C1: 1.62 (SE = 0.14, t = 11.45, $p < 0.001$) and C2: -0.27 (SE = 0.03, t = -8.36, $p < 0.001$). Both groups showed significant changes in internet addiction levels over time, with C1 showing a significant increase and C2 showing a significant decrease.

Analysis of intercept and slope means indicated that C1 had a higher initial level that increased significantly over time, while C2 had a lower initial level that decreased significantly over time. Based on these patterns, the two latent classes were named: C1 Risk Group, comprising 11.65% of the sample (n = 149), and C2 Normal Group, comprising 88.35% of the sample (n = 1,130). The growth trajectories for the two-class model are shown in Figure 1 [Figure 1: see original paper]. Demographic information and group differences at initial assessment are presented in Appendix Table 1.

Table 3 GMM Fit Information

Model	Log(L)	Entropy	LMR p-value	BLRT p-value	Class Probabilities (%)
1-class			<0.001	<0.01	100
2-class			<0.001	<0.01	11.65/88.35
3-class			<0.001	<0.01	79.59/16.42/3.99
4-class			0.15	0.20	80.77/7.90/7.82/3.52
5-class			0.10	0.15	74.51/13.45/7.66/2.74/1.64

Note: T1 = October–November 2016 (7th grade); T2 = October–November 2017 (8th grade); T3 = October–November 2018 (9th grade). Risk group: n = 149 (11.65%); Normal group: n = 1,130 (88.35%).

3.3 Network Analysis

3.3.1 Network Estimation and Comparison To further understand symptom evolution in the risk group, network analysis was used to estimate symptom network structures and summarize change patterns among risk group adolescents (n = 149). Since the addicted and non-addicted groups distinguished by mean internet addiction scores at each time point showed significant differences across all internet addiction symptoms, mean internet addiction scores at each time point were included as covariates in network estimation following Van Borkulo et al. (2015). Additionally, since age showed limited discrimination within the risk group, only gender was included as a covariate in network analysis. To facilitate comparison across the three time points, all three symptom networks used identical node layouts. Each network formed 55 edges ($11 \times (11\text{-}1)/2$). The T1 network had 14 non-zero weight edges, while T2 and T3 had 17 and 8 non-zero weight edges, respectively. Average network densities across the three time points were 0.25, 0.30, and 0.15, indicating strongest symptom connections at T2 and weakest at T3. Symptom networks at the three time points are shown in Figure 2 [Figure 2: see original paper].

Network comparison analysis using permutation tests further compared network structure, global strength, and edge differences across the three time points. Results (see Table 4) showed no significant differences in network structure ($p = 0.99$) or global strength ($p = 0.55$) between T1 and T2, no significant difference in network structure between T1 and T3 ($p = 0.38$) but significant difference in global strength ($p < 0.05$), and similarly no significant difference in network structure between T2 and T3 ($p = 0.27$) but significant difference in global strength ($p < 0.05$). Local permutation results from network comparison analysis revealed that only the connection between "Negative Consequences" (A6) and "Concealment" (A7) significantly weakened between T1 and T2 ($p < 0.01$), with no other edges showing significant differences. Between T1 and T3, significant differences were found for edges between "Compulsive Internet Use" (A1) and "Lack of Satisfaction" (A2, $p < 0.001$) and between "Negative Consequences" (A6) and "Concealment" (A7, $p < 0.05$). From T2 to T3, numerous edges significantly weakened over time, including those between "Compulsive Internet Use" (A1) and "Lack of Satisfaction" (A2, $p < 0.001$), "Loss of Control" (A3) and "Excessive Time Use" (A5, $p < 0.01$), "Loss of Control" (A3) and "Concealment" (A7, $p < 0.05$), and "Loss of Control" (A3) and "Lack of Satisfaction" (A2, $p < 0.05$).

Table 4 Cross-Time-Point Network Comparison Results

Comparison	Network Structure p-value	Global Strength p-value	Significant Edge Differences
T1 vs. T2	0.99	0.55	A6-A7 (weakened)
T1 vs. T3	0.38	<0.05	A1-A2, A6-A7
T2 vs. T3	0.27	<0.05	A1-A2, A3-A5, A3-A7, A2-A3

Note: A1 = Compulsive Internet Use; A2 = Lack of Satisfaction; A3 = Loss of Control; A4 = Emotional Dyscontrol; A5 = Excessive Time Use; A6 = Negative Consequences; A7 = Concealment; A8 = Escape Reality; A9 = Withdrawal Symptoms; A10 = Excessive Money Use. a = Values calculated from network comparison analysis of difference scores. b = Only edges with significant differences (p < 0.05) are listed.

3.3.2 Centrality Estimation Strength centrality for the risk group across three time points is shown in Figure 3 [Figure 3: see original paper]. In seventh grade, "Compulsive Internet Use" (A1), "Lack of Satisfaction" (A2), "Emotional Dyscontrol" (A4), and "Withdrawal Symptoms" (A9) all showed strong centrality, indicating these symptoms were tightly connected with other symptoms at this time point. In eighth grade, "Lack of Satisfaction" (A2) showed the highest strength centrality across all three time points, becoming the core symptom. In ninth grade, "Withdrawal Symptoms" (A9) showed a renewed upward trend after declining in eighth grade, becoming the core symptom at this time point. Other centrality indices across the three time points are provided in Supplementary Figure 1.

3.3.3 Network Accuracy and Stability Tests Results from the edge weight bootstrap procedure are shown in Figure 4 [Figure 4: see original paper], indicating relatively accurate edge estimation for all three networks: except for edges between covariates and internet addiction symptoms, there was minimal overlap in 95% CIs for remaining edge weights. Bootstrap results calculating differences in strongest edges are provided for reference (see Supplementary Figure 2), showing few significant differences between edges and suggesting caution in interpreting edge differences. Centrality stability coefficients (CS-coefficients) were estimated through subset bootstrap procedures. Results showed that CS-coefficients for strength centrality across the three time points were 0.51, 0.59, and 0.45, respectively. Subset bootstrap results are shown in Supplementary Figure 3.

Discussion

This study used GMM analysis to explore adolescent internet addiction trajectories, identify at-risk groups, and employed network analysis to compare symptom network evolution characteristics across time points among risk group adolescents, identifying core symptoms at each stage. Results confirmed Hypothesis 1, demonstrating that adolescent internet addiction trajectories exhibit group heterogeneity, with a risk group showing increasing internet use behaviors that eventually develop into internet addiction. Additionally, network analysis results indicated that connections between internet addiction symptoms among risk group adolescents were strongest in eighth grade, with different core symptoms emerging at different stages: "Compulsive Internet Use," "Lack of Satisfaction," "Emotional Dyscontrol," and "Withdrawal Symptoms" occupied high centrality positions in seventh grade; "Lack of Satisfaction" became the most central core symptom in eighth grade, with the highest strength centrality across all three time points; as addictive behavior formed, "Withdrawal Symptoms" became the core symptom in ninth grade. By combining the advantages of GMM and network analysis, this study provides new perspectives and insights for identifying and understanding adolescents in the internet addiction risk group, offering strong empirical evidence for developing targeted intervention programs.

4.1 Identification of the Internet Addiction Risk Group GMM results showed that adolescents could be divided into normal and risk groups based on internet addiction trajectories. The normal group comprised 88.35% of the sample, with low initial internet addiction scores that remained stable from T1 to T2 and slowly declined from T2 to T3. The risk group comprised 11.65% of the sample, with initial addiction levels significantly higher than the normal group. Although this group remained relatively stable between T1 and T2, scores increased rapidly from T2 to T3, with the group's average exceeding the clinical threshold by T3, indicating high potential risk.

Specifically, although both normal and risk group adolescents showed relatively stable low addiction levels in seventh and eighth grades, the two groups showed distinctly different patterns after eighth grade: the normal group showed slight declines while the risk group showed rapid increases. This may be because eighth grade represents a critical developmental period when adolescents experience peak physical and psychological changes, with dramatic shifts in psychology and behavior—what previous research has termed the "8th-grade phenomenon" (also called "chuuni-byo" or "middle school second-year syndrome"; Shen & Zhang, 2011). The "8th-grade phenomenon" refers to the frequent emergence of increased negative emotions, decreased self-esteem, and lower life satisfaction after adolescents enter eighth grade (Lu et al., 2009; Deng et al., 2015). According to the "failure compensation hypothesis" (Gao & Chen, 2006), normal group adolescents likely possess adequate positive resources (e.g., stable and positive peer relationships, good family atmosphere, and personal psychological qualities) that enable them to actively seek effective resources to meet their adaptive needs when facing negative impacts of the "8th-grade phenomenon." As these positive resources increase, the internet's appeal gradually decreases (Lee et al., 2001), leading to "constructive compensation." Therefore, after the adaptive period, this group's internet use behaviors gradually decrease. For risk group adolescents, when facing the "8th-grade phenomenon," the internet may become an important pathway to escape real-life difficulties due to their lack of positive resources, with positive experiences from internet use further reinforcing their internet dependence (Schimmenti et al., 2017; Yee, 2006), forming "pathological compensation" and eventually leading to internet addiction.

4.2 Core Symptoms of the Internet Addiction Risk Group To identify intervention targets at different periods, this study used network analysis to explore symptom network evolution in the risk group and identify core symptoms at each time point. Compared to previous adolescent internet addiction network analysis research, this study supplements findings with longitudinal data. Specifically, although Liu et al. (2022) found no significant differences in network structure and global strength across early (7th–8th grade), middle (9th–10th grade), and late (11th–12th grade) adolescence, their study used a cross-sectional design comparing symptom networks across adolescents at different pubertal stages to indicate group trends. However, because adolescents' internet use behaviors vary individually across pubertal stages, group trends may mask time-related differences in symptom networks. In contrast, this study's longitudinal design addresses this limitation, supplementing empirical evidence on how adolescent internet addiction symptom networks and symptom strength change over time. This study found that global strength among risk group adolescents was highest at T2, followed by T1, and lowest at T3. No significant differences were found in network structure or global strength between T1 and T2. Although no significant differences in network structure were found between T1, T2, and T3, global strength at T3 was significantly stronger than at T1 and T2. According to psychopathological network theory, increased global strength means that when one symptom is activated, other symptoms are more easily activated, manifesting as disease deterioration (Robinaugh et al., 2020). Accordingingly, as connections between internet addiction symptoms among risk group adolescents strengthened from eighth to ninth grade, internet addiction showed a worsening trend during this period. This finding corresponds with internet addiction trajectory results, jointly suggesting that eighth grade represents a critical inflection point for risk group formation and addiction deterioration.

Second, centrality estimation results for the risk group's symptom networks across three time points indicated different core symptoms at different stages. In seventh grade, risk group adolescents showed four high-centrality core symptoms: "Compulsive Internet Use," "Lack of Satisfaction," "Emotional Dyscontrol," and "Withdrawal Symptoms." This may be because adolescents newly entering middle school maintain high curiosity and exploration of novel things while also adapting to new learning environments, making internet use an important way to satisfy curiosity and adapt to new school life (Arnone et al., 2009). Since the internet can provide positive and novel emotions and experiences (Zhang & Bian, 2021), compared to difficulties faced in the real world and accompanying lack of satisfaction, high-frequency internet use can effectively meet their emotional needs. Therefore, when these adolescents attempt to reduce or stop internet use, the resulting negative experiences may contrast sharply with positive online experiences, making them prone to emotional dyscontrol or withdrawal symptoms and increasing their dependence on the internet. In eighth grade, the centrality of "Lack of Satisfaction" further increased to the highest point across all three time points, becoming the core symptom. This suggests that internet use among risk group adolescents represents compensatory behavior for dealing with lack of satisfaction caused by the "8th-grade phenomenon." When these adolescents' social needs, needs to cope with negative emotions, and self-actualization needs cannot be appropriately met, the internet may become their best source of satisfaction (Cai et al., 2007; Liu et al., 2016). Therefore, as a critical time point in adolescence, eighth grade is key for preventing risk group adolescents from developing "pathological compensation" by teaching them proper ways to satisfy their needs. In ninth grade, the core symptom for risk group adolescents was "Withdrawal Symptoms." Consistent with previous research, withdrawal symptoms have long been considered prominent symptoms of internet addiction (Giordano et al., 2020; Kaptsis et al., 2016). At this time point, risk group adolescents have gradually formed internet addiction, making withdrawal symptoms the core symptom. For these adolescents, internet use may have become their primary or even sole means of satisfying their needs. Therefore, when they stop using the internet, perceived negative emotions (e.g., emptiness, loneliness, helplessness, depression) and problem behaviors become particularly prominent. Additionally, previous research indicates that persistent internet addiction damages adolescents' cognitive brain function (Hong et al., 2013), thereby reducing problem-solving abilities (Say & Batigun, 2016). Long-term internet addiction may lead these adolescents to become numb to other problems caused by internet use (e.g., financial issues, time management problems, academic performance). Consequently, compared to negative consequences of internet use, withdrawal symptoms become prominently manifested at this stage.

4.3 Study Limitations This study has several limitations to be addressed in future research. First, since all variables were measured through self-report, despite our efforts to ensure participant anonymity and include validity checks, this method still cannot overcome biases inherent in subjective reporting, affecting data accuracy. Future research should consider incorporating multi-informant data from teachers and parents. Second, this study's sample was limited to public school adolescents and cannot represent all adolescent populations (e.g., private and vocational school students), and the three-year follow-up covered only middle school, limiting generalizability to other age groups. Future research should expand the sample range and design longer-term follow-ups (e.g., from 7th through 12th grade) to further test or extend these findings. Finally, since academia has not reached consensus on defining internet addiction symptoms, this study's symptom analysis was based on scale items. Future research should refine the classification of internet addiction symptoms and test the conclusions of this study.

4.4 Conclusions and Implications Based on internet addiction trajectories, this study found that adolescents showing risky developmental patterns of internet addiction prominently exhibited four symptoms when first entering middle school (7th grade): "Compulsive Internet Use," "Lack of Satisfaction," "Emotional Dyscontrol," and "Withdrawal Symptoms." Subsequently, during the high-risk middle school stage (8th grade), "Lack of Satisfaction" became prominently manifested, with symptoms most tightly connected. As overall addictive behavior developed and solidified, "Withdrawal Symptoms" became the most prominent symptom in 9th grade, representing later-stage addiction.

Based on these findings, this study argues that interventions for risk group adolescents should not only focus on post-diagnosis intervention but also on the process of addiction formation. Importantly, clinicians and school administrators should include internet addiction in student mental health records, regularly survey student internet addiction status, and establish dynamic management mechanisms. This study proposes a "Three-Prevention" strategy ("Prevention"-"Warning"-"Intervention") for addressing adolescent internet addiction risk. First, the period from 7th to 8th grade serves as the "Prevention" stage. During this stage, although normal and risk groups differ in addiction severity, the difference is not large, and neither group has reached the clinical threshold. Therefore, this stage should focus on risk prevention—for example, school mental health education curricula can educate students about proper internet use behaviors and negative consequences of internet addiction, and rich campus or community life can divert students' needs and attention from the internet. Notably, the prominent roles of "Compulsive Internet Use," "Lack of Satisfaction," "Emotional Dyscontrol," and "Withdrawal Symptoms" from 7th to 8th grade suggest we should focus on adolescents' curiosity and satisfaction, guiding them to properly alleviate negative emotional reactions when stopping internet use. Additionally, longitudinal research has found that poor school adaptation in 7th grade increases internet addiction rates in 9th grade (Bu et al., 2021). Therefore, embedding prevention work within traditional elementary-to-middle school transition counseling may provide intervention space within existing school frameworks to prevent problems before they occur. Second, 8th grade should serve as the critical "Warning" stage for internet addiction. As the key time point when normal and risk groups diverge, identifying potential internet addiction risk during this stage is particularly important. "Lack of Satisfaction" as the core symptom for risk group adolescents in 8th grade suggests that educators and clinicians should use adolescents' satisfaction deficits as a key identification criterion, closely monitoring internet use behaviors of adolescents lacking satisfaction, focusing early warning on students showing internet addiction in 7th grade, and implementing targeted monitoring measures when necessary to help adolescents learn appropriate internet use and adopt positive methods (e.g., sports, reading, social activities) to satisfy their needs. Additionally, since family environment is not only a risk factor for the occurrence and persistence of adolescent internet addiction (Bu et al., 2021) but also an important source of adolescent satisfaction, leveraging home-school cooperation functions, timely warnings to parents, and enhancing parental awareness for joint prevention are also important means of systematically addressing adolescent internet addiction. Finally, the "Intervention" stage occurs in 9th grade when risk group adolescents' addictive behavior has formed. Therefore, intervention measures should focus on withdrawal symptoms to help adolescents overcome current internet addiction withdrawal, using approaches such as cognitive-behavioral therapy, mindfulness interventions, exercise interventions, and family therapy to help students overcome internet addiction, stop being lost in the "net," and avoid more severe psychological and behavioral consequences.

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Appendices

Appendix Table 1. Demographic Information for Normal and Risk Groups at Initial Assessment

Variable	Normal Group (n = 1130)	Risk Group (n = 149)
Age (initial)		
Father's Education: Junior high or below		
Father's Education: High school or above		
Mother's Education: Junior high or below		
Mother's Education: High school or above		

Supplementary Figure 1. Betweenness and Closeness Indices Across Three Networks

Supplementary Figure 2. Edge Strength Difference Tests Across Three Networks
Note: T = Mean internet addiction score at each time point; G = Gender; black boxes indicate significant differences between two nodes.

Supplementary Figure 3. Subset Bootstrap Results Across Three Networks
Note: T = Mean internet addiction score at each time point; G = Gender.

Note: Figure translations are in progress. See original paper for figures.