Changes in the comorbidity patterns of negative emotional symptoms and Internet addiction over time among the first-year senior high school students: A one-year longitudinal study

Tingting Gao[a,b,c,d,e], Leilei Liang[c], Muzi Li[d,e], Yingying Su[d,e], Songli Mei[c], Chengchao Zhou[a,b], Xiangfei Meng[d,e]

[a] Center for Health Management and Policy Research, School of Public Health, Cheeloo College of Medicine, Shandong University, Jinan, Shandong, China

[b] NHC Key Lab of Health Economics and Policy Research, Shandong University

[c] School of Public Health, Jilin University, Changchun, Jilin, China

[d] Department of Psychiatry, Faculty of Medicine, McGill University, Montreal, Quebec, Canada

[e] Douglas Mental Health University Institute, Montreal, Quebec, Canada

***Corresponding author:**
*Songli Mei, School of Public Health, Jilin University, 1163 Xinmin Street, Changchun, Jilin, 130021, China (meisongli@sina.com);

*Chengchao Zhou, Center for Health Management and Policy Research, School of Public Health, Cheeloo College of Medicine, Shandong University, 44 Wenhuaxi Rd, Jinan, Shandong, 250012, China (zhouchengchao@sdu.edu.cn);

This is the accepted manuscript of Gao, T., Liang, L., Li, M., Su, Y., Mei, S., Zhou, C., & Meng, X. (2022). Changes in the comorbidity patterns of negative emotional symptoms and Internet addiction over time among the first-year senior high school students: A one-year longitudinal study. Journal of Psychiatric Research, 155, 137–145. [*https://doi.org/10.1016/j.jpsychires.2022.08.020*](https://doi.org/10.1016/j.jpsychires.2022.08.020)

Abstract

Background: The comorbidity of psychiatric disorders and IA has been widely documented. However, changes and instability of the comorbidity between negative emotional symptoms and IA over time are not fully understood. **Methods:** A sample of 453 first-year senior high school students completed all measures three times across one-year period and were included in the current study. The sample consisted of 163 (36.0%) males and 290 (64.0%) females. At the baseline, the mean age of the participants was 15.07±0.46 (range: 12-16) years old. Latent class analysis was used to identify the latent class pattern. Multinomial logistic regression analysis was utilized to examine the association between covariates and latent classes at baseline. Latent transition analysis was applied to explore the changes in latent classes of individuals over time. **Results:** Three subgroups of negative emotional symptoms, IA and their comorbidity were identified at all the three time points. Being Internet gamers, high average time of Internet use every day, peer exclusion, verbal and physical bullying experience, and poor self-rated health were found to be significant predictors of the high comorbidity symptom. Students were more likely to remain the same class rather than moving between the latent classes across time. **Conclusions:** A better understanding of change characteristics in latent classes across time contributes to confirm an appropriate time for intervention targeted on students who converted from low symptom class to the high class.

Key words: Negative emotional symptoms; Internet addiction; comorbidity; Latent class analysis; Latent transition analysis

1. Introduction

Depression and anxiety are common mental health problems and often co-occur during adolescence

(Feiss et al., 2019). Depression, anxiety and behavioral disorders are the leading causes of illnesses and disability among adolescents (WHO, 2021a). World Health Organization (WHO, 2021b) estimated that around 20.0% of children and adolescents had at least one mental health condition in the world, with a peak increase in overall prevalence of depression during middle-to-late adolescence (Sunderland et al., 2021). There was 34.0% of adolescents globally reporting depressive symptoms from 2001 to 2020 (Shorey et al., 2021). The pooled prevalence of anxiety among adolescents was 9.0% (Biswas et al., 2020). Adolescent depression and anxiety disorders were likely to continue into adulthood and were associated with a series of adverse outcomes, including suicidal behavior (Soto-Sanz et al., 2019), poor academic performance (Awadalla et al., 2020) and impaired mental health (Johnson et al., 2018).

Excessive use of the Internet has become a serious public health concern in a growing number of countries (WHO, 2018). Internet addiction (IA), sometimes called compulsive Internet use, problematic Internet use, pathological Internet use or excessive Internet use, represents a behavioral addiction due to uncontrolled Internet consumption (Tokunaga and Rains, 2016). There is a lack of agreement with regard to the operationalization for IA. IA is generally characterized by excessive or loss of control over internet use that generates functional impairment or distress feelings (Shaw and Black, 2008). Internet gaming disorder (IGD), a specific form of IA, is defined as "persistent and recurrent use of the internet to engage in games, often with other players, leading to impairment or clinically significant distress" by American Psychiatric Association (2013). A systematic review and meta-analysis of epidemiology covering studies from 31 countries revealed that the pooled prevalence of generalized internet addiction was about 7.0% and the prevalence was increased over time (Pan et al., 2020). A pooled prevalence of 20.0% for IA was found in Southeast Asia (Chia et al., 2020). Adolescents with IA displayed a various of health-related problems, including internalizing and externalizing problems, and poor academic performance (Marciano et al., 2022). Cardiopulmonary-related deaths in Internet cafes and game-related murders could be also the results of IA (Block, 2008).

When students started their first year in high schools, they face a range of new social and academic demands (Reinke and Herman, 2002). In China, senior high school is a crucial period for students, as they are often exposed to great academic pressures due to national competitions to be enrolled at an ideal university. Adolescence is a vital era for significant developmental tasks such as emotional and cognitive capacities, as well as the formation of life-long connections, but also for risk behavior and susceptibility, which is why it is important to identify adolescents prone to digital threats such as IA and mental health (Clark et al., 2020; Kickbusch et al., 2021; WHO, 2021a).

The comorbidity of psychiatric disorders and IA has been widely documented (Kim et al., 2016; Weinstein and Lejoyeux, 2010). The pooled prevalence of depression in individuals with IGD was 32% (Ostinelli et al., 2021). Adolescents with IA had the prevalence of 71.7% for anxiety disorder and 30.0% for major depressive disorder (Bozkurt et al., 2013). Previous studies suggested that negative emotional symptoms and IA have some common features, such as suicidal ideation (Park et al., 2013; Zheng et al., 2021), negative school outcomes (Hashim et al., 2012; Jun, 2019), and sleep problems (Lam, 2014; Zochil and Thorsteinsson, 2018). Moreover, IA and depression shared similar comorbid conditions in genetic and personality traits (Lee et al., 2008). Both individuals with IA and those suffering from mood disorders exhibited dysfunctions in dopaminergic pathways (Caldiroli et al., 2018). The theory of compensatory internet use argued that excessive internet use may compensate for psychosocial problems (Kardefelt-Winther, 2014). It might be the reason why negative emotional symptoms and IA often overlap.

Many studies have applied variable-centered approaches to examine the co-occurrence of psychiatric disorders and IA (Kim et al., 2016; Weinstein and Lejoyeux, 2010). These approaches, such as regression analysis, factor analysis, and structural equation modeling, mainly focus on the relationships among variables (Muthén and Muthén, 2000). This method assumes that the sample is from homogenous population and classifies the whole sample into subgroups by the cut points of total scores for variable, which ignore the individuals' actual response to all questions (Haltigan and Vaillancourt, 2018; Nylund, 2007). Whereas person-centered approaches, such as latent class analysis (LCA), mainly describe relationships among individuals, aiming at classifying individual into different subgroups or latent classes based on the response pattern of observed categorical variables (Muthén and Muthén, 2000). LCA provides an insight to identify distinct subtypes by more scientific methods and measures, which makes this classification more accuracy and better explains the nature of the research question (Nylund, 2007). LCA has been deemed appropriate in comorbid symptoms of depression and anxiety (Rudenstine and Espinosa, 2018; van Lang et al., 2006), and internet-related studies (Lee et al., 2018; Tullett-Prado et al., 2021). Though a growing body of research on depression, anxiety and IA, the present study will be one of the few to fill gaps in interindividual complexity regarding the comorbidity patterns of negative emotional symptoms and IA.

Although previous studies have suggested that several factors are associated with an increased risk of negative emotional symptoms (e.g., depression, anxiety) (Cummings et al., 2014; Konac et al., 2021), IA (Chi et al., 2020; Shen et al., 2020), and their comorbidity (Gao et al., 2020) among adolescents, there is still a lack of research conducted to explore comorbidity patterns of these negative emotional symptoms and IA using person-centered approaches. An in-depth understanding of unique and common factors associated with mental health problems allows for targeted preventive and intervention strategies to be developed.

Longitudinal studies have observed that IA was not stable and would change over time among adolescents (Jia et al., 2021; Li et al., 2019). The dynamic systems theory supports that one state of a system moves to another state across time and there is a comorbidity between internalizing and externalizing behavior (Mascolo et al., 2016). Therefore, it is important to explore changes and instability of the comorbidity between negative emotional symptoms and IA over time. The changes in negative emotional symptoms, IA and their comorbidity that occur during adolescence have important implications for preventive strategies aiming at decreasing poor clinical outcomes and disease burden. Different control measures could be incorporated according to the changes. To the best of our knowledge, no studies have explored transitions on the comorbidity between negative emotional symptoms and IA.

The present study aims to identify latent groups of negative emotional symptoms and IA and to explore changes in these latent classes among three repeated measurements among adolescents. Based on the latent class of negative emotional symptoms and IA at baseline, we would like to determine which adolescents might be at higher risk for such comorbidity. The better understanding of transition contributes to clarify the necessity and possibility of interventions at reducing the comorbidity of negative emotional symptoms and IA over time.

2. Methods

2.1 Participants and procedure

The data used in current study were from a survey conducted in a high school in Changchun, China and started in the October 2017. Using random cluster sampling method, we selected 2,272 students from grade 10 to 12 at the first time point (T1). The follow-up data were collected for the 10^{th} students approximately every six months. The participants who completed the measures of covariates at baseline, Depression Anxiety Stress Scales (DASS-21) and Young's diagnostic questionnaire (YDQ) at baseline (T1), 6 months (T2) and 12 months (T3) were included in the present study. A total of 453 students in the grade 10 finished the three-wave data collection. More details about the sampling procedure have been published elsewhere (Gao et al., 2020). The sample consisted of 163 (36.0%) males and 290 (64.0%) females. At the baseline, the mean age of the participants was 15.07±0.46 (range: 12-16) years old. Over half of students had an average monthly pocket money less than 300 RMB (n=267, 58.9%). The majority of participants had no sibling (n=330, 72.8%) and lived in urban (n=412, 90.9%).

The ethical approval was received from the ethics committee of Jilin University for the present study before data collection. All the students and their parents or guardian provided the informed consent. Participants were reminded that their participation were voluntary and they had the right to withdraw their participation at any time. Questionnaires were required to finish in the designated classroom and returned after being completed by the participants. Each survey took around 20 minutes to complete.

2.2 Measures

2.2.1 Depression Anxiety Stress Scales

We used the Depression and Anxiety subscale of Chinese version of DASS-21 (Gong et al., 2010) to evaluate the negative emotional symptoms, which was originally developed in 1995 (Lovibond and Lovibond, 1995). Seven items for each dimension measured depression (i.e., “I felt that I had nothing to look forward to”) and anxiety (i.e., “I felt I was close to panic”) symptoms, separately. Participants rated the extent to which certain experiences applied to them over the past week on a 4-point Likert scale ranging from 0 (did not apply to me at all) to 3 (applied to me very much or most of the time). The total score was calculated by summing all the item scores, with higher scores indicate greater negative emotional symptoms. We dichotomized the response as “did not apply to me at all” and “applied to me”. Three subscales of DASS-D (α_{t1}=0.75, α_{t2}=0.87, α_{t3}=0.90) and DASS-A (α_{t1}=0.70, α_{t2}=0.84, α_{t3}=0.95) had acceptable internal consistencies at each time point (T1, T2, and T3).

2.2.2 Young's diagnostic questionnaire

The 8-item Young's diagnostic questionnaire (YDQ) (Young, 1998) was used to assess IA. Total scores range from 0 to 8 with a higher score indicates a severe level of IA. Participants with more than four scores were classified as having IA. This scale had acceptable internal consistency at each time point (α_{t1}=0.71, α_{t2}=0.78, α_{t3}=0.82).

2.2.3 Covariates

We also considered the following sociodemographic, Internet use and experiences of peer bullying characteristics at baseline as covariates in the multinomial logistic regression model. Sex (1=female, 2=male), age, family residence (1=urban, 2=rural), whether have siblings (1=Yes, 2=No), and the average monthly pocket money (1= less than or equal to 300 RMB, 2=more than 300 RMB) were the studied demographics. The question, "Are you an Internet gamer currently?", was used to evaluate whether participants involved in Internet gaming. The question to measure the time of Internet use was as follow, "In the past month, how long have you used the Internet averagely every day on weekdays and weekends, respectively?" Average time of Internet use every day was calculated by this equation: (Average Internet use time on weekdays×5 + Average Internet use time on weekend×2)/7. According to the recommendation of top and bottom 27% of the overall score distribution (Kelley, 1939), average time of Internet use every day was defined as low (⩽24 minutes), moderate (25-72 minutes) and high (>72 minutes) Internet use. Items of bullying victimization was adapted from verbal bullying, physical bullying and relational bullying dimension of the Chinese version of Delaware Bullying Victimization Scale-Student (DBVS-S) separately (Xie et al., 2015), which was originally developed by Bear et al. (2011). Peer exclusion was determined by being rejected by peers at school during the past six months prior to the data collection. Verbal bullying was measured by being laughed at by peers at school. Physical bullying was determined by being deliberately beaten, kicked, pushed, or bumped by peers at school. Participants were also asked to rate their overall health (1=good, 2=moderate, 3=poor).

2.3 Statistical analysis

LCA is a person-oriented approach and suitable for cross-sectional data analysis. It is used to identify the latent class (Nylund, 2007). First, the optimal number of underlying subgroups for negative emotional symptoms, IA and their comorbidity at each time point was selected according to the model fit criteria. Lower Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and adjusted BIC (aBIC) values represent better model fit (Tofighi & Enders, 2007). The value of entropy greater than 0.80 reflects better classification accuracy (Clark, 2010). Besides, the significant *p*-value of Lo-Mendell-

Rubin Likelihood Ratio Test (LMR-LRT) and the Bootstrapped Likelihood Ratio Test (BLRT) are also required (Nylund et al., 2007). LCA model mainly estimates two parameters including conditional item-response probability and class-membership probability. Secondly, multinomial logistic regression analysis was used to examine the association between covariates and latent classes at baseline. Lastly, we fixed the same latent classes based on the results of LCA, which presented the same characteristics in each latent class across the three time points (Paik et al., 2020). The repeated-measures LCA (RMLCA) does not fit a functional form to change over time, which can be fit in the latent classes corresponding to different patterns of categorical or discrete change across several time points (Collins and Lanza, 2010). Latent transition analysis (LTA), a longitudinal extension of LCA, was applied to explore the changes in latent classes of individuals between two adjacent times (Nylund, 2007). LTA, also a type of latent Markov model, has an advantage over estimation of transition probability from one time to the next. In order to improve identification and make the results more interpretable, the item-response probabilities are constrained to be equal over time in LTA model (Collins & Lanza, 2010). The stationary assumption in LTA imposes the probability of transitioning among latent classes that are the same or remain constant across the study period (Nylund, 2007). The transition probability was generated by the unconditional LTA to describe the probability of movement among the latent status for negative emotional symptoms, IA and their comorbidity between two time points. All the missing was random. The full information maximum likelihood (FIMI) approach was applied to handle the missing data. All the analyses were conducted in the software of Mplus 8.3 (Muthén and Muthén, 1998-2017) and SPSS 24.0.

3. Results

3.1. Model selection at each time point

The number of latent classes of negative emotional symptoms and IA and their comorbidity at T1, T2 and T3 was selected, separately. Table S1 presents the fit statistics for possible latent statuses in the LCA model. The lower AIC, BIC, aBIC values and the significant *p*-value of LMR-LRT supported a 3-class solution as the LCA model for negative emotional symptoms, IA, and their comorbidity at each data collection except the comorbidity at T3. While the four-class model had a smaller AIC, BIC, aBIC values and higher Entropy value than three-class model for the comorbidity of negative emotional symptoms and IA at T3, the 3-class model was selected considering the consistency in LTA measurement models.

3.2. Defining the latent classes

The latent classes of negative emotional symptoms, IA, and their comorbidity at T1, T2 and T3 are displayed in Fig. 1. The latent classes of studied variables were defined based on the item response probability. We define the lines with square markers as “high negative emotional symptoms”, “problematic users” and “high comorbidity symptom”, respectively. They represent the classes that had the highest probability of endorsing negative emotional symptoms, IA, and their comorbidity, respectively. Participants were classified into the “moderate negative emotional symptoms” with moderate estimated probability of endorsing negative emotional symptoms from T1 to T3, using the lines with triangle markers to label. “Moderate risk users” and “moderate comorbidity symptom” were labeled. “Low negative emotional symptoms” referred to individuals who were more likely to have the lowest probability of endorsing any of the negative emotional symptoms at each data collection that was plotted by lines with circle markers. “No-risk users” (<0.28) and “low comorbidity symptom” (<0.44) with lowest probabilities were also labeled.

3.3. Correlates of negative emotional symptoms, IA, and their comorbidity at baseline

Multinomial logistic regression analysis was used to explore the association between characteristics and latent classes of negative emotional symptoms, IA, and their comorbidity at baseline, using the “low negative emotional symptoms”, “no-risk users” and “low comorbidity symptom” as the reference class for each model, respectively. Table 1 shows that Internet gamer, average time of Internet use every day, peer bullying and self-rated health were the significant predictors of negative emotional symptoms, IA and their comorbidity latent classes at baseline ($p<0.05$).

3.4. Changes in the latent classes of negative emotional symptoms, IA, and their comorbidity among high school students

Table 2 displays the latent class prevalence in each time point and transition probabilities across the two adjacent times. Most students were classified into the moderate negative emotional symptoms class at T1 (n=246, 54.30%), and the proportion of this latent class declined over time (n=157, 34.66% for T2; n=133, 29.36% for T3), particularly from T1 to T2. In contrast, the proportion of low negative emotional symptoms class increased over time (n=180, 39.74% for T1; n=193, 42.60% for T2; n=237, 52.32% for T3). The high negative emotional symptoms class maintained as the lowest proportion at each data collection. The similar pattern was also observed for IA and the comorbidity. At each data collection, the problematic users class had the lowest proportion. Participants in the no-risk users class increased, whereas the moderate risk users class declined over time. The high comorbidity of negative emotional symptoms and IA class maintained the lowest proportion at each data collection. The number of students who were classified into the moderate comorbidity class decreased, whereas numbers of those in the low comorbidity class increased across time.

The transition probabilities were used to explore how change occurred between latent classes from T1 (row) to T2 (column) and T2 (row) to T3 (column). The highest probability of being the same latent classes was 0.886 (0.951) for the low negative emotional symptoms class, 0.575 (0.614) for the moderate negative emotional symptoms class, and 0.794 (0.577) for the high negative emotional symptoms class from T1 to T2 (T2 to T3), respectively. Individuals in the moderate negative emotional symptoms class had a higher probability of transitioning to the low and high class over time. More importantly, students in the high negative emotional class showed a higher probability of transitioning into the moderate class over time. In general, most students in the no-risk users class (T1 to T2: 0.830, T2 to T3: 0.903), moderate risk users class (T1 to T2: 0.744, T2 to T3: 0.727) and problematic users class (T1 to T2: 0.865, T2 to T3: 0.730) were more likely to remain unchanged over time. Except for transition in no-risk users and problematic users class, there was a high transition probability for bidirectional movement among other classes. The highest probability of remaining in the same class for the low comorbidity class, the moderate comorbidity class and the high comorbidity class was 0.838 (0.926), 0.600 (0.675) and 0.848 (0.624) from T1 to T2 (T2 to T3), respectively. Those in the moderate comorbidity class with the probability of 30.3% changed into the high comorbidity class from T1 to T2. In addition, there was a similar probability with nearly 20% of transition from moderate comorbidity class to the low class and high symptom to the moderate class from T2 to T3.

Figure 2 illustrates the latent class movement patterns for IA, negative emotional symptoms, and their comorbidity across three data collections. The largest proportion of participants (n=157, 34.7%) were more likely to remained in the low negative emotional symptoms class at all the three data collections, followed by the moderate class (n=96, 21.2%). Those in moderate negative emotional symptoms class at T1 were most likely to move to the high class at T2 and T3 (n=42, 9.3%), whose proportion was larger than those in the high class at all three data collections. As for latent class patterns of IA, the majority of students were inclined to stay in the same class over time and ranked as moderate risk users (n=140, 30.9%), no-risk users (n=118, 26.0%) and problematic users (n=52, 11.5%) class.

Participants who remained in the moderate symptom class at T1 and T2 had higher likelihood of moving to the low class at T3 (n=43, 9.5%). With regard to the movement pattern for comorbidity, most students in the low (n=123, 27.2%) and moderate (n=113, 24.9%) symptom class tended to remain in the same class across time. We also found a large proportion of students who were in the moderate class at T1, moved to high class at T2 and T3.

4. Discussion

The present study provides for the first time the evidence on latent classes of negative emotional symptoms, IA, and their comorbidity and changes in these latent classes with a 1-year follow-up among adolescents. We identified three latent classes of negative emotional symptoms, IA, and their comorbidity, separately. These latent classes remained the same at the three-wave data collections. Those who were Internet gamers, had more than average time of Internet use every day, exposed to peer bullying, and poor self-rated health, were correlated with negative emotional symptoms, IA, and their comorbidity.

Prior work identified three latent classes in mood disorders (Weiss et al., 2021). We also identified three distinct classes, consisting of high, moderate and low negative emotional symptoms. Using the measure of YDQ, three distinct subgroups of students were replicated (Hirota et al., 2021). According to the characteristics of each item endorsement, we defined these subgroups as problematic users, moderate risk users and no-risk users class, respectively. In terms of comorbidity between negative emotional symptoms and IA, this differed from findings in the patterns of depressive and externalizing symptoms (Mezulis et al., 2011). Three latent classes of negative emotional symptoms and IA with high, moderate and low comorbidity symptom were identified in the present study.

Internet gaming addicts have been found to exhibit increased emotional difficulties, including depression, anxiety and social isolation (Stockdale and Coyne, 2018). Previous study has repeatedly shown online game playing was highly correlated with IA, in particular some similarities and relationships between behavioral addictions may be the main reason (Gunuc, 2015). In accordance with the displacement hypothesis, it costs individuals increased time on one medium and declined time would be spent in other medium (Nie et al., 2002). Excessive time spent online could reduce the time of face-to-face communication and offline social interaction might contribute to mood symptoms (Liang et al., 2016). Thus, spending more time on online activities may increase the risk of IA (Mo et al., 2020) and negative emotions (Liang et al., 2016). Those exposed to peer exclusion and verbal bullying experiences were important correlates of IA and comorbidity of negative emotional symptoms with IA. Negative mood was a common response to negative peer experiences (peer victimization and exclusion) (Reavis et al., 2015). Similar association between peer victimization and problematic Internet use in adolescents have been reported in the previous studies (Boniel-Nissim and Sasson, 2018; Zhai et al., 2019). Based on the social compensation theory (Valkenburg and Peter, 2009), excessive Internet use was a strategy of coping negative feelings from adverse life situations. This finding is consistent with prior studies that poor self-rated health was a significant predictor of IA (Ha and Hwang, 2014) and mental health (Riddle and Dumenci, 2013).

We also found that the proportion of low negative emotional symptoms, IA, and their comorbidity classes increased over time. Research on the developmental trajectories revealed all classes of anxiety symptoms declined, while depressive symptoms remained stable across a one-year period during early adolescence (McLaughlin and King, 2015). Similarly, latent curve modeling found problematic internet use were inclined to follow a decreasing trajectory over a 3-year period in late adolescence (Tóth-Király et al., 2021). In contrast, moderate negative emotional symptoms, IA, and their comorbidity of individuals decreased over time. Thus, a proportion of students in this latent class moved to low or high symptoms class across time. The higher transition probability of moderate latent class further supported the above results. Moderate early symptoms (moderate high level initially and decrease over time) and late symptoms (low level initially and increase over time) of depression trajectories were identified by a latent class growth analysis in Australian adolescence (Ellis et al., 2017). Students with moderate level of negative emotions may be more likely to experience changes over time. In addition, most students were more likely to be in the primary latent class over time, which was in line with the research on the co-morbidity of depression, anxiety and fatigue (Zhu et al., 2017). The transition probabilities indicated students with IA displayed higher level of being the same class during one-year period. More than 70% students in the problematic users class would remain the same class, which was similar to the results from a 2-year prospective study (Hirota et al., 2021). For the comorbidity, over 60% of students remained in the same class across all three time points. The latent class movement patterns for IA, negative emotional symptoms, and their comorbidity also demonstrated that most of participants remained in the same class and accounted for large proportion over one year. In order to prevent the persistence of symptoms, the prompt interventions were targeted at this population exhibited more symptoms. It is noteworthy that the severity of symptom had a certain degree of variability, especially the transition between the low and high class. Findings of higher probability in the bidirectional transition among some certain classes were of significance, especially for the important role of moderate class played in this transition. The optimal timing of interventions were made to promote the healthy transition. The latent class movement patterns over one year call attention to those who were in the moderate class at T1, then movde to high class at T2 and T3 for negative emotional symptoms and comorbidity.

Practical implications and limitations

We identified the latent classes of emotional symptoms, IA and their comorbidity, and characteristics associated with a higher risk of these mental and behavioral problems. These findings could inform effective interventions. Attention should be prioritized to students with high risk of negative emotional symptoms or IA. Moreover, the findings highlighted relevant help should be given to Internet gamer, individuals with higher average time of Internet use every day, peer bullying experiences and poor self-rated health. Lastly, students were more likely to remain the same class rather than moving between the latent classes across time. These findings emphasize the importance of adopting targeted interventions for students with severe symptoms. While it is important to consider the health gradient as a whole, we should ensure that the impact of the interventions benefits the most vulnerable adolescents. So, in other words, to promote equity over equality by prioritizing disadvantaged groups in the intervention development (e.g., targeted interventions) by proportionate universalism (Marmot and Bell 2012). Adolescence is a period of significant changes in physical, psychological and social development. A better understanding of change characteristics in latent classes across time contributes to confirm an appropriate time for intervention targeted on students who converted from low symptom class to the moderate or high class.

This study also has several limitations. First, we only followed the first-year senior high school students across one year. The whole period of senior high school maybe reflect the transition of negative emotional symptoms, IA, and their comorbidity more accurately. Second, self-report measures were used in the present study, which might have measurement bias. Adolescents often overly emphasize the amount of their internet activity; thus, sufficiently objective view is hard to get with self-report instruments (Parry et al., 2021). The findings could benefit more from a more objective measure in the future. Third, the present study mainly focused on the negative effect of excessive Internet use, IA, while Internet is also facilitated to daily life for users in many aspects (e.g. make it convenient to communicate without the limit of time and place). Last, the sample was from one senior high school of China. The generalization of findings will be limited. More representative samples from cross-cultural background will be considered in the future research.

Conclusion

In summary, the present study extended the current knowledge regarding the heterogeneity and nature of negative emotional symptoms, IA and their comorbidity. We identified three subgroups of each symptom at all the three time points. Those who were Internet gamers, had more than average time of Internet use every day, exposed to peer bullying, and poor self-rated health, were correlated with negative emotional symptoms, IA, and their comorbidity. The priority should be given to those exposed to more above-mentioned risk factors. Considering the longitudial transition of these latent classes in each symptom over a period of one year, students in the high symptom classes with higher probability of being the same class were the main intervention population.

Acknowledgements

We would like to thank all the participants in the present study. This research was supported by the Humanities and Social Sciences Youth Fund of the Ministry of Education of China (21YJC630028), Natural Science Foundation of Shandong Province (ZR2021QG052), China Postdoctoral Science Foundation (2021M691909), Shandong Social Science Planning Fund Program (21CSZJ31) and the Fonds de la recherche en sante du Quebec, Canada.

Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article:

Table S1. Model fit indices of LCA for negative emotional symptoms, IA, and their comorbidity at each data collection.

Reference

American Psychiatric Association, 2013. Diagnostic and Statistical Manual of Mental disorders (5th ed). Washington, D.C., American Psychiatric Association, pp.795.

Awadalla, S., Davies, E.B., Glazebrook, C., 2020. A longitudinal cohort study to explore the relationship between depression, anxiety and academic performance among Emirati university students. BMC Psychiatry 20, 448. https://doi.org/10.1186/s12888-020-02854-z.

Bear GG, Gaskins C, Blank J, Chen, F.F., 2011. Delaware School Climate Survey—Student: Its factor structure, concurrent validity, and reliability. J. Sch. Psychol. 49, 157-174. https://doi.org/10.1016/j.jsp.2011.01.001.

Biswas, T., Scott, J.G., Munir, K., Renzaho, A.M.N., Rawal, L.B., Baxter, J., Mamun, A.A., 2020. Global variation in the prevalence of suicidal ideation, anxiety and their correlates among adolescents: A population based study of 82 countries. EClinicalMedicine 24, 100395. https://doi.org/10.1016/j.eclinm.2020.100395.

Block, J.J., 2008. Issues for DSM-V: Internet addiction. Am. J. Psychiatry 165, 306-307. https://doi.org/10.1176/appi.ajp.2007.07101556

Boniel-Nissim, M., Sasson, H., 2018. Bullying victimization and poor relationships with parents as risk factors of problematic internet use in adolescence. Comput. Hum. Behav. 88, 176-183. https://doi.org/10.1016/j.chb.2018.05.041.

Bozkurt, H., Coskun, M., Ayaydin, H., Adak, İ., Zoroglu, S.S., 2013. Prevalence and patterns of psychiatric disorders in referred adolescents with Internet addiction. Psychiatry Clin. Neurosci. 67, 352-359. https://doi.org/10.1111/pcn.12065.

Caldiroli, A., Serati, M., Buoli, M., 2018. Is Internet addiction a clinical symptom or a psychiatric disorder? A comparison with bipolar disorder. J. Nerv. Ment. Dis. 206, 644-656. https://doi.org/10.1097/NMD.0000000000000861.

Chi, X., Hong, X., Chen, X., 2020. Profiles and sociodemographic correlates of Internet addiction in early adolescents in southern China. Addict. Behav. 106, 106385. https://doi.org/10.1016/j.addbeh.2020.106385.

Chia, D.X.Y., Ng, C.W.L., Kandasami, G., Seow, M.Y.L., Choo, C.C., Chew, P.K.H., Lee, C., Zhang, M.W.B., 2020. Prevalence of Internet addiction and gaming disorders in Southeast Asia: A meta-analysis. Int. J. Environ. Res. Public Health 17, 2582. https://doi.org/10.3390/ijerph17072582.

Clark, H., Coll-Seck, A.M., Banerjee, A., Peterson, S., Dalglish, S.L., Ameratunga, S., Balabanova, D., Bhan, M.K., Bhutta, Z.A., Borrazzo, J., Claeson, M., Doherty, T., El-Jardali, F., George, A.S., Gichaga, A., Gram, L., Hipgrave, D.B., Kwamie, A., Meng, Q., Mercer, R., Narain, S., Nsungwa-Sabiiti, J., Olumide, A.O., Osrin, D., Powell-Jackson, T., Rasanathan, K., Rasul, I., Reid, P., Requejo, J., Rohde, S.S., Rollins, N., Romedenne, M., Sachdev, H.S., Saleh, R., Shawar, Y.R., Shiffman, J., Simon, J., Sly, P.D., Stenberg, K., Tomlinson, M., Ved, R.R., Costello, A., 2020. A future for the world's children? A WHO–UNICEF–Lancet Commission. Lancet 395, 605-658. https://doi.org/10.1016/S0140-6736(19)32540-1.

Clark, S.L., 2010. Mixture modeling with behavioral data. Los Angeles, CA: University of California.

Collins, L.M., Lanza, S.T., 2010. Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences. John Wiley & Sons, Inc.

Cummings, C.M., Caporino, N.E., Kendall, P.C., 2014. Comorbidity of anxiety and depression in children and adolescents: 20 years after. Psychol. Bull. 140, 816-845. https://doi.org/10.1037/a0034733.

Ellis, R.E.R., Seal, M.L., Simmons, J.G., Whittle, S., Schwartz, O.S., Byrne, M.L., Allen, N.B., 2017. Longitudinal trajectories of depression symptoms in adolescence: Psychosocial risk factors and outcomes. Child Psychiatry Hum. Dev. 48, 554-571. https://doi.org/10.1007/s10578-016-0682-z.

Feiss, R., Dolinger, S.B., Merritt, M., Reiche, E., Pangelinan, M., 2019. A systematic review and meta-analysis of school-based stress, anxiety, and depression prevention programs for adolescents. J. Youth Adolesc. 48, 1668-1685. https://doi.org/10.1007/s10964-019-01085-0.

Gao, T., Li, M., Hu, Y., Qin, Z., Cao, R., Mei, S., Meng, X., 2020. When adolescents face both Internet addiction and mood symptoms: A cross-sectional study of comorbidity and its predictors. Psychiatry Res. 284, 112795. https://doi.org/10.1016/j.psychres.2020.112795.

Gong, X., Xie, X., Xu, R., Luo, Y., 2010. Psychometric properties of the Chinese versions of DASS-21 in Chinese college sudents. Chinese Journal of Clinical Psychology (in Chinese), 18, 443-446. https://doi.org/10.16128/j.cnki.1005-3611.2010.04.020

Gunuc, S., 2015. Relationships and associations between video game and Internet addictions: Is tolerance a symptom seen in all conditions. Comput. Hum. Behav. 49, 517-525. https://doi.org/10.1016/j.chb.2015.03.063.

Ha, Y.M., Hwang, W.J., 2014. Gender differences in Internet addiction associated with psychological health indicators among adolescents using a national web-based survey. Int. J. Ment. Health Addict. 12, 660-669. https://doi.org/10.1007/s11469-014-9500-7.

Haltigan, J.D., Vaillancourt, T., 2018. The influence of static and dynamic intrapersonal factors on longitudinal patterns of peer victimization through mid-adolescence: a latent transition analysis. J. Abnorm. Child Psychol. 46, 11-26. https://doi.org/10.1007/s10802-017-0342-1.

Hashim, H.A., Freddy, G., Rosmatunisah, A., 2012. Relationships between negative affect and academic achievement among secondary school students: The mediating effects of habituated exercise. J. Phys. Act. Health 9, 1012-1019. https://doi.org/10.1123/jpah.9.7.1012.

Hirota, T., Takahashi, M., Adachi, M., Sakamoto, Y., Nakamura, K., 2021. Neurodevelopmental traits and longitudinal transition patterns in internet addiction: A 2-year prospective study. J. Autism Dev. Disord. 51, 1365-1374. https://doi.org/10.1007/s10803-020-04620-2.

Jia, J., Tong, W., Zhang, J., Liu, F., Fang, X., 2021. Trajectory of problematic internet use across the college years: The role of peer internet overuse behavior and peer attitude toward internet overuse. J. Adolesc. 86, 64-76. https://doi.org/10.1016/j.adolescence.2020.12.006.

Johnson, D., Dupuis, G., Piche, J., Clayborne, Z., Colman, I., 2018. Adult mental health outcomes of adolescent depression: A systematic review. Depression Anxiety 35, 700-716. https://doi.org/10.1002/da.22777.

Jun, S., 2019. Longitudinal influences of depressive moods on problematic mobile phone use and negative school outcomes among Korean adolescents. Sch. Psychol. Int. 40, 294-308. https://doi.org/10.1177/0143034319830452.

Kardefelt-Winther, D., 2014. A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. Comput. Hum. Behav. 31, 351-354. https://doi.org/10.1016/j.chb.2013.10.059.

Kelley, T.L., 1939. The selection of upper and lower groups for the validation of test items. J. Educ.

Psychol. 30, 17-24. https://doi.org/10.1037/h0057123.
Kickbusch, I., Piselli, D., Agrawal, A., Balicer, R., Banner, O., Adelhardt, M., Capobianco, E., Fabian, C., Singh Gill, A., Lupton, D., Medhora, R., Ndili, N., Ryś, A., Sambuli, N., Settle, D., Swaminathan, S., Morales, J.V., Wolpert, M., Wyckoff, A.W., Xue, L., 2021. The Lancet and Financial Times Commission on governing health futures 2030: growing up in a digital world. Lancet 398, 1727-1776. https://doi.org/10.1016/S0140-6736(21)01824-9.
Kim, B.S., Chang, S.M., Park, J.E., Seong, S.J., Won, S.H., Cho, M.J., 2016. Prevalence, correlates, psychiatric comorbidities, and suicidality in a community population with problematic Internet use. Psychiatry Res. 244, 249-256. https://doi.org/10.1016/j.psychres.2016.07.009.
Konac, D., Young, K.S., Lau, J., Barker, E.D., 2021. Comorbidity between depression and anxiety in adolescents: bridge symptoms and relevance of risk and protective factors. J. Psychopathol. Behav. Assess. 43, 583-596. https://doi.org/10.1007/s10862-021-09880-5.
Lam, L.T., 2014. Internet gaming addiction, problematic use of the internet, and sleep problems: a systematic review. Curr. Psychiatry Rep. 16, 444. https://doi.org/10.1007/s11920-014-0444-1.
Lee, S.-Y., Lee, D., Nam, C.R., Kim, D.Y., Park, S., Kwon, J.-G., Kweon Y.-S., Lee Y., Kim D.J., Choi J.-S, 2018. Distinct patterns of Internet and smartphone-related problems among adolescents by gender: Latent class analysis. J. Behav. Addict. 7, 454-465. https://doi.org/10.1556/2006.7.2018.28.
Lee, Y.S., Han, D.H., Yang, K.C., Daniels, M.A., Na, C., Kee, B.S., Renshaw, P.F., 2008. Depression like characteristics of 5HTTLPR polymorphism and temperament in excessive internet users. J. Affective Disord. 109, 165-169. https://doi.org/10.1016/j.jad.2007.10.020.
Li, G., Hou, G., Yang, D., Jian, H., Wang, W., 2019. Relationship between anxiety, depression, sex, obesity, and internet addiction in Chinese adolescents: A short-term longitudinal study. Addict. Behav. 90, 421-427. https://doi.org/10.1016/j.addbeh.2018.12.009.
Liang, L., Zhou, D., Yuan, C., Shao, A., Bian, Y., 2016. Gender differences in the relationship between internet addiction and depression: A cross-lagged study in Chinese adolescents. Comput. Hum. Behav. 63, 463-470. https://doi.org/10.1016/j.chb.2016.04.043.
Lovibond, P.F., Lovibond, S.H., 1995. The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. Behav. Res. Ther. 33(3), 335-343. https://doi.org/10.1016/0005-7967(94)00075-U.
Marciano, L., Camerini, A.L., Schulz, P.J., 2022. Neuroticism and internet addiction: What is next? A systematic conceptual review. Pers. Individ. Differ. 185, 111260. https://doi.org/10.1016/j.paid.2021.111260.
Marmot, M., Bell, R., 2012. Fair society, health lives. Public Health 126, S4-S10. https://doi.org/10.1016/j.puhe.2012.05.014.
Mascolo, M.F., Geert, P.V., Steenbeek, H., Fischer, K.W., 2016. What can dynamic systems models of development offer to the study of developmental psychopathology? John Wiley & Sons, Inc.
McLaughlin, K.A., King, K., 2015. Developmental trajectories of anxiety and depression in early adolescence. J. Abnorm. Child Psychol. 43, 311-323. https://doi.org/10.1007/s10802-014-9898-1.
Mezulis, A., Stoep, A.V., Stone, A.L., Mccauley, E., 2011. A latent class analysis of depressive and externalizing symptoms in nonreferred adolescents. J. Emot. Behav. Disord. 19, 247-256. https://doi.org/10.1177/1063426610377763.
Mo, P.K.H., Chan, V.W.Y., Wang, X., Lau, J.T.F., 2020. Gender difference in the association between

internet addiction, self-esteem and academic aspirations among adolescents: A structural equation modelling. Comput. Educ. 155, 103921. https://doi.org/10.1016/j.compedu.2020.103921.
Muthén, B., Muthén, L.K., 2000. Integrating person-centered and variable-centered analyses: growth mixture modeling with latent trajectory classes. Alcohol. Clin. Exp. Res. 24, 882-891. https://doi.org/10.1111/j.1530-0277.2000.tb02070.x.
Muthén, L.K., Muthén, B.O., (1998-2017). Mplus user's guide (Eighth Edition). Los Angeles, CA: Muthén & Muthén.
Nie, N. H., Sunshine Hillygus, D., Erbring, L., 2002. Internet use, interpersonal relations, and sociability. B. Wellman, C. Haythornthwaite (Eds.), The Internet in everyday life, Blackwell Publisher, UK.
Nylund, K.L., 2007. Latent transition analysis: Modeling extensions and an application to peer victimization (Ph.D.). University of California, Los Angeles.
Nylund, K.L., Asparouhov, T., Muthén, B.O., 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. Struct. Equ. Model. 14, 535-569. https://doi.org/10.1080/10705510701575396.
Ostinelli, E.G., Zangani, C., Giordano, B., Maestri, D., Gambini, O., D'Agostino, A., Furukawa, T.A., Purgato, M., 2021. Depressive symptoms and depression in individuals with internet gaming disorder: A systematic review and meta-analysis. J. Affective Disord. 284, 136-142. https://doi.org/10.1016/j.jad.2021.02.014.
Paik, I.S., Ahn, S., Lee, S.M., 2020. Longitudinal adaptive pattern analysis of child abuse victims during childhood and adolescence. Psychol. Rep. 123, 2125-2146. https://doi.org/10.1177/0033294119857437.
Pan, Y.C., Chiu, Y.C., Lin, Y.H., 2020. Systematic review and meta-analysis of epidemiology of internet addiction. Neurosci. Biobehav. Rev. 118, 612-622. https://doi.org/10.1016/j.neubiorev.2020.08.013.
Park, S., Hong, K.E.M., Park, E.J., Ha, K.S., Yoo, H.J., 2013. The association between problematic internet use and depression, suicidal ideation and bipolar disorder symptoms in Korean adolescents. Aust. New Zealand J. Psychiatry 47, 153-159. https://doi.org/10.1177/0004867412463613.
Parry, D.A., Davidson, B.I., Sewall, C.J., Fisher, J.T., Mieczkowski, H., Quintana, D.S., 2021. A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. Nat. Hum. Behav. 5, 1535-1547. https://doi.org/10.1038/s41562-021-01117-5.
Reavis, R.D., Donohue, L.J., Upchurch, M.C., 2015. Friendship, negative peer experiences, and daily positive and negative mood. Soc. Dev. 24, 833-851. https://doi.org/10.1111/sode.12123.
Reinke, W.M., Herman, K.C., 2002. Creating school environments that deter antisocial behaviors in youth. Psychol. Sch. 39, 549-559. https://doi.org/10.1002/pits.10048.
Riddle, D.L., & Dumenci, L., 2013. Self-rated health and symptomatic knee osteoarthritis over three years: Data from a multicenter observational cohort study. Arthritis Care Res. 65, 169-176. https://doi.org/10.1002/acr.21661.
Rudenstine, S., Espinosa, A., 2018. Latent comorbid depression and anxiety symptoms across sex and race/ethnic subgroupings in a national epidemiologic study. J. Psychiatr. Res. 104, 114-123. https://doi.org/10.1016/j.jpsychires.2018.07.005.
Shaw, M., Black, D.W., 2008. Internet addiction: Definition, assessment, epidemiology and clinical

management. CNS Drugs, 22, 353-365. https://doi.org/10.2165/00023210-200822050-00001.
Shen, Y., Meng, F., Xu, H., Li, X., Zhang, Y., Huang, C., Luo, X., Zhang, X. Y. (2020). Internet addiction among college students in a Chinese population: Prevalence, correlates, and its relationship with suicide attempts. Depression Anxiety, 37, 812-821. https://doi.org/10.1002/da.23036.
Shorey, S., Ng, E.D., Wong, C.H.J., 2022. Global prevalence of depression and elevated depressive symptoms among adolescents: A systematic review and meta-analysis. Br. J. Clin. Psychol. 61, 287-305. https://doi.org/10.1111/bjc.12333.
Soto-Sanz, V., Castellví, P., Piqueras, J.A., Rodríguez-Marín, J., Rodríguez-Jiménez, T., Miranda-Mendizábal, A., Parés-Badell, O., Almenara, J., Alonso, I., Blasco, M.J., Cebrià, A., Gabilondo, A., Gili, M., Lagares, C., Roca, M., Alonso, J. (2019). Internalizing and externalizing symptoms and suicidal behaviour in young people: a systematic review and meta-analysis of longitudinal studies. Acta Psychiatr. Scand. 140, 5-19. https://doi.org/10.1111/acps.13036.
Stockdale, L., Coyne, S.M., 2018. Video game addiction in emerging adulthood: Cross-sectional evidence of pathology in video game addicts as compared to matched healthy controls. J. Affective Disord. 225, 265-272. https://doi.org/10.1016/j.jad.2017.08.045.
Sunderland, M., Champion, K., Slade, T., Chapman, C., Newton, N., Thornton, L., Kay-Lambkin, F., McBride, N., Allsop, S., Parmenter, B., Teesson, M., Health4Life Team, 2021. Age-varying associations between lifestyle risk factors and major depressive disorder: a nationally representative cross-sectional study of adolescents. Soc. Psychiatry Psychiatr. Epidemiol. 56, 129-139. https://doi.org/10.1007/s00127-020-01888-8.
Tofighi, D., Enders, C.K., 2007. Identifying the correct number of classes in growth mixture models. In G.R. Hancock & K. M. Samuelsen (Eds.), Charlotte, NC: Information Age.
Tokunaga, R.S., Rains, S.A., 2016. A review and meta-analysis examining conceptual and operational definitions of problematic Internet use. Hum. Commun. Res. 42, 165-199. https://doi.org/10.1111/hcre.12075.
Tóth-Király, I., Morin, A.J.S., Hietajärvi, L., Salmela-Aro, K., 2021. Longitudinal trajectories, social and individual antecedents, and outcomes of problematic internet use among late adolescents. Child Dev. 92, e653-e673. https://doi.org/10.1111/cdev.13525.
Tullett-Prado, D., Stavropoulos, V., Mueller, K., Sharples, J., Footitt,T.A., 2021. Internet Gaming Disorder profiles and their associations with social engagement behaviours. J. Behav. Addict. 138, 393-403. https://doi.org/10.1016/j.jpsychires.2021.04.037.
Valkenburg, P.M., Peter, J., 2009. Social consequences of the Internet for adolescents: A decade of research. Curr. Dir. Psychol. Sci. 18, 1-5. https://doi.org/10.1111/j.1467-8721.2009.01595.x.
van Lang, N.D.J., Ferdinand, R.F., Ormel, J., Verhulst, F.C., 2006. Latent class analysis of anxiety and depressive symptoms of the Youth Self-Report in a general population sample of young adolescents. Behav. Res. Ther. 44(6):849-860. https://doi.org/10.1016/j.brat.2005.06.004.
Weinstein, A., Lejoyeux, M., 2010. Internet addiction or excessive Internet use. Am. J. Drug Alcohol Abuse 36, 277-283. https://doi.org/10.3109/00952990.2010.491880.
Weiss, S.J., Flynn, H., Christian, L., Hantsoo, L., di Scalea, T.L., Kornfield, S.L., Muzik M., Simeonova, D.I., Cooper, B.A., Strahm, A., Deligiannidis, K.M., 2021. Symptom profiles of women at risk of mood disorders: A latent class analysis. J. Affective Disord. 295, 139-147. https://doi.org/10.1016/j.jad.2021.08.013.
WHO, 2018. Public health implications of excessive use of the Internet and other communication and gaming platforms. [cited 2021 December 2]. Available from:

https://www.who.int/news/item/13-09-2018-public-health-implications-of-excessive-use-of-the-internet-and-other-communication-and-gaming-platforms.

WHO, 2021a. Adolescent mental health. [cited 2021 December 2]. Available from: https://www.who.int/news-room/fact-sheets/detail/adolescent-mental-health.

WHO, 2021b. Mental health. [cited 2021 December 2]. Available from: https://www.who.int/health-topics/mental-health#tab=tab_2.

Xie, J., Lv, Y., Bear, G.G., Yang, C., Marshall, S.J., Gong, R., 2015. Reliability and validity of the Chinese version of Delaware Bullying Victimization Scale-Student. Chinese Journal of Clinical Psychology 23, 594-596. https://doi.org/10.16128/j.cnki.1005-3611.2015.04.006.

Young, K.S., 1998. Internet addiction: the emergence of a new clinical disorder. Cyberpsychol. Behav. 1, 237-244. https://doi.org/10.1089/cpb.1998.1.237.

Zhai, B., Li, D., Jia, J., Liu, Y., Sun, W., Wang, Y., 2019. Peer victimization and problematic internet use in adolescents: The mediating role of deviant peer affiliation and the moderating role of family functioning. Addict. Behav. 96, 43-49. https://doi.org/10.1016/j.addbeh.2019.04.016.

Zheng, F., Wu, W., Wang, L., Ngoubene-Atioky, A.J., Chen, L., 2021. Childhood trauma and suicidal ideation among Chinese female prisoners: The mediating roles of negative emotions and social support. Pers. Individ. Differ. 168, 110405. https://doi.org/10.1016/j.paid.2020.110405.

Zhu, L., Ranchor, A.V., van der Lee, M., Garssen, B., Almansa, J., Sanderman, R., Schroevers, M.J., 2017. Co-morbidity of depression, anxiety and fatigue in cancer patients receiving psychological care. Psycho-Oncology, 26, 444-451. https://doi.org/10.1002/pon.4153.

Zochil, M.L., Thorsteinsson, E.B., 2018. Exploring poor sleep, mental health, and help-seeking intention in university students. Aust. J. Psychol. 70, 41-47. https://doi.org/10.1111/ajpy.12160.

Table 1 Predictors of IA latent classes at baseline/T1

	Negative emotional symptoms		IA		Comorbidity	
	Moderate symptom OR (95% CI)	High symptom OR (95% CI)	Moderate symptom OR (95% CI)	High symptom OR (95% CI)	Moderate symptom OR (95% CI)	High symptom OR (95% CI)
Internet gamer						
No	1	1	1	1	1	1
Yes	1.61 (1.05-2.46) **	1.79 (0.88-3.65)	1.63 (1.05-2.54)*	2.28 (1.20-4.33)*	1.80 (1.14-2.82)	3.17 (1.66-6.06)***
Average time of Internet use every day						
Low	1	1	1	1	1	1
Moderate	1.19 (0.72-1.97)	1.59 (0.63-4.03)	2.01 (1.22-3.33)**	3.40 (1.44-8.04)**	2.08 (1.23-3.52)**	1.71 (0.79-3.69)
High	2.08 (1.16-3.73)*	5.10 (1.93-13.48)**	4.37 (2.31-8.26)***	11.25 (4.38-28.88)***	4.16 (2.16-7.80)***	6.97 (2.97-16.34)***
Peer exclusion						
No	1	1	1	1	1	1
Yes	2.22 (1.01-4.95)	9.37 (3.75-23.38)***	1.51 (0.66-3.48)	3.51 (1.36-9.06)**	2.03 (0.78-5.27)	5.16 (1.85-14.42)**
Verbal bullying						
No	-	-	1	1	1	1
Yes	-	-	2.13 (1.16-3.91)*	3.20 (1.50-6.82)**	1.80 (0.95-3.42)	3.03 (1.41-6.48)**
Physical bullying						
No	1	1	-	-	1	1
Yes	2.03 (0.75-5.45)	6.33 (2.03-19.74)**	-	-	1.85 (0.62-5.54)	3.74 (1.11-12.61)*
Self-rated health						
Good	1	1	1	1	1	1
Moderate	1.81 (1.15-2.84)*	2.70 (1.26-5.78)*	1.18 (0.73-1.91)	1.69 (0.86-3.34)	1.79 (1.09-2.93)*	3.04 (1.54-6.01)**
Poor	5.29 (2.54-11.03)***	7.00 (2.51-19.58)***	1.94 (0.96-3.91)	2.92 (1.20-7.16)*	4.28 (1.84-9.96)**	10.49 (3.92-28.09)***

Note. Low Negative emotional symptoms class, low IA symptom class and low comorbidity symptom class are the reference latent class for each category multinomial logistic regression model.

-Variables are not included in the final model.

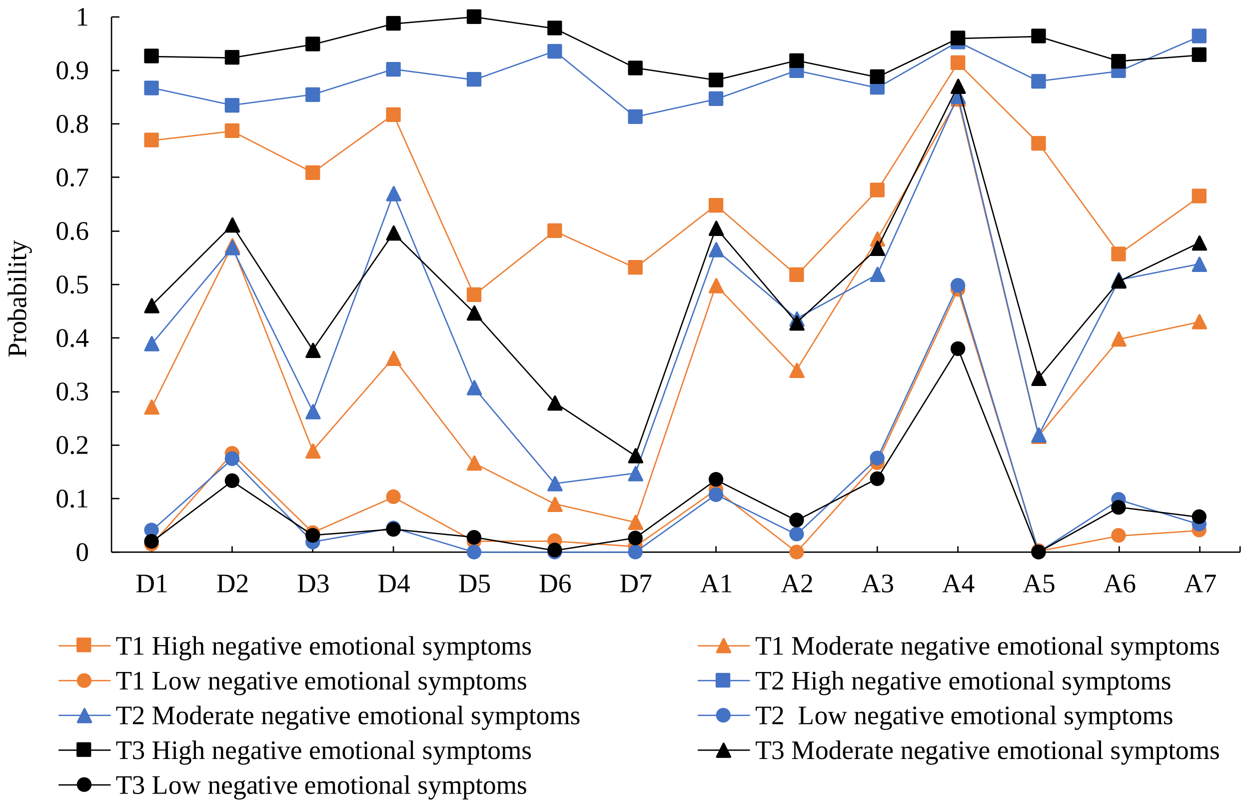
* p<0.05; ** p<0.01; *** p<0.001.

Table 2 Latent class prevalence and transition probabilities of class changes over time

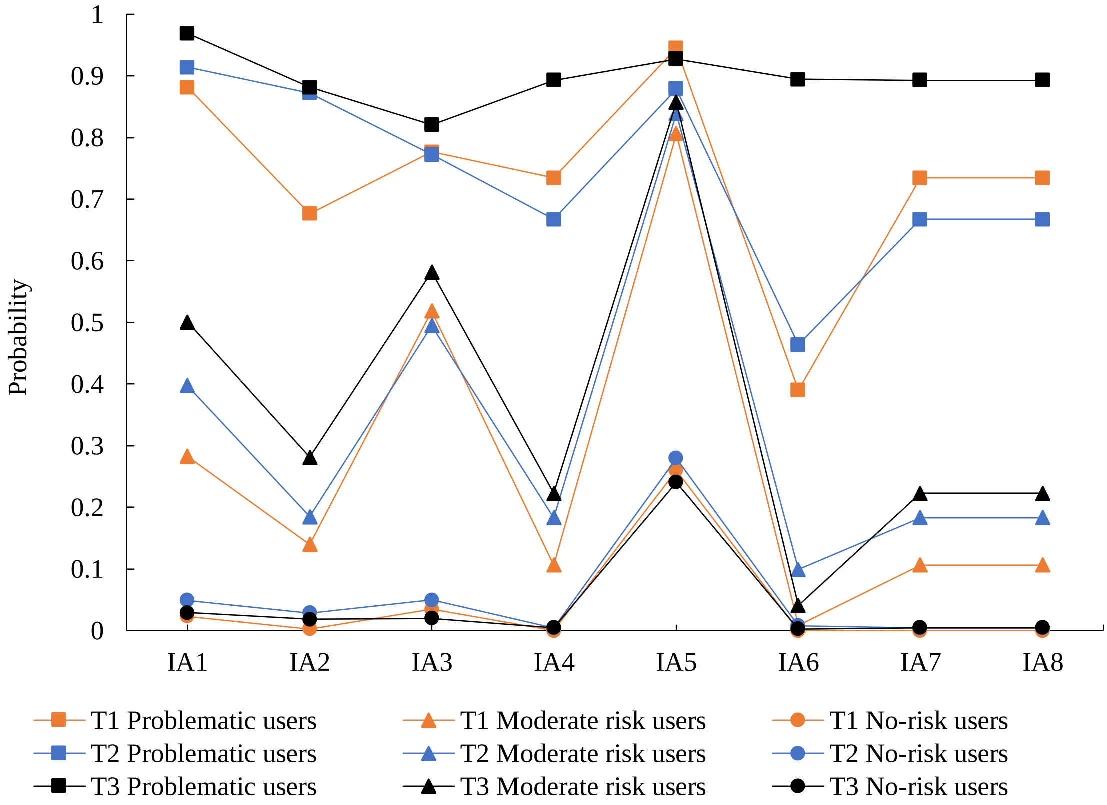
	Latent classes		
Negative emotional symptoms	Low symptom	Moderate symptom	High symptom
Latent class prevalence			
T1	180 (39.74%)	246 (54.30%)	27 (5.96%)
T2	193 (42.60%)	157 (34.66%)	103 (22.74%)
T3	237 (52.32%)	133 (29.36%)	83 (18.32%)
Transition probabilities#	T2 (T3)		
T1 (T2)			
Low symptoms	**0.886 (0.951)**	0.062 (0.036)	0.052 (0.013)
Moderate symptoms	0.123 (0.246)	**0.575 (0.614)**	0.301 (0.139)
High symptoms	0.054 (0.170)	0.151 (0.253)	**0.794 (0.577)**
IA	Low symptom	Moderate symptom	High symptom
Latent class prevalence			
T1	141 (31.13%)	247 (54.52%)	65 (14.35%)
T2	161 (35.54%)	202 (44.59%)	90 (19.87%)
T3	204 (45.03%)	167 (36.87%)	82 (18.10%)
Transition probabilities#	T2 (T3)		
T1 (T2)			
Low symptom	**0.830 (0.903)**	0.118 (0.081)	0.053 (0.017)
Moderate symptom	0.142 (0.221)	**0.744 (0.727)**	0.114 (0.052)
High symptom	0.024 (0.069)	0.111 (0.201)	**0.865 (0.730)**
Comorbidity of negative emotional symptoms and IA	Low symptom	Moderate symptom	High symptom
Latent class prevalence			
T1	152 (33.55%)	255 (56.29%)	46 (10.16%)
T2	157 (34.66%)	170 (37.53%)	126 (27.81%)
T3	199 (43.93%)	152 (33.55%)	102 (22.52%)
Transition probabilities#	T2 (T3)		
T1 (T2)			
Low symptoms	**0.838 (0.926)**	0.101 (0.061)	0.061 (0.013)
Moderate symptoms	0.097 (0.200)	**0.600 (0.675)**	0.303 (0.125)
High symptoms	0.043 (0.159)	0.108 (0.217)	**0.848 (0.624)**

Note. # Transition matrix from T1 (T2) to T2 (T3); Rows for T1 (T2), columns for T2 (T3). Transition probabilities in bold indicates the highest probability of remaining in the same class from one-time point to the next.

(1) The estimated probability of nagative emotional symptoms by latent classes at T1, T2 and T3



(2) The estimated probability of IA by latent classes at T1, T2 and T3



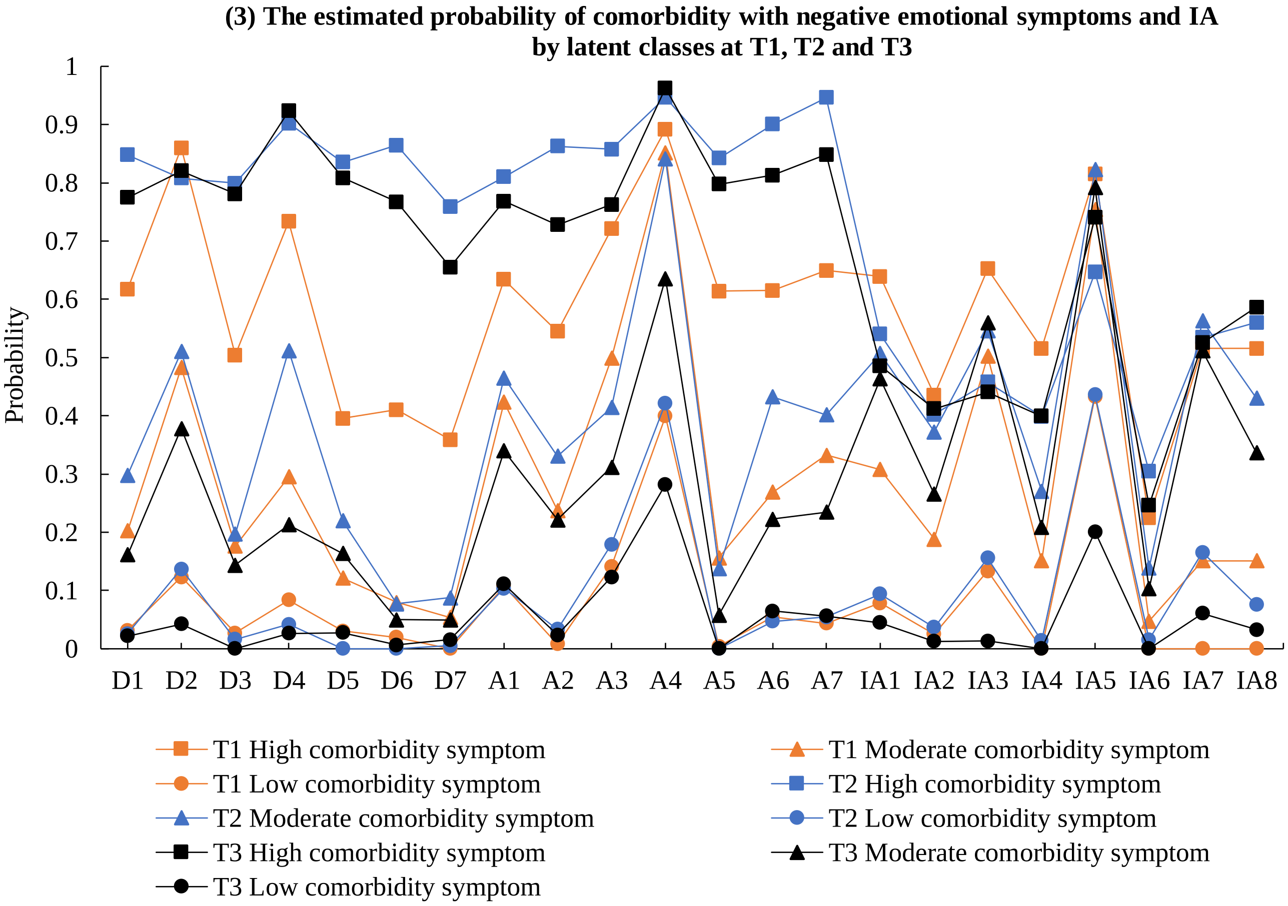
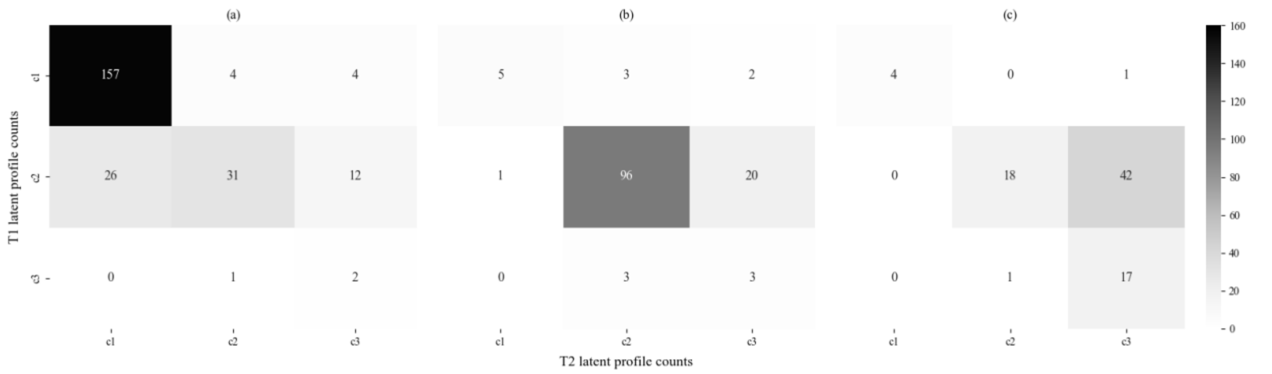


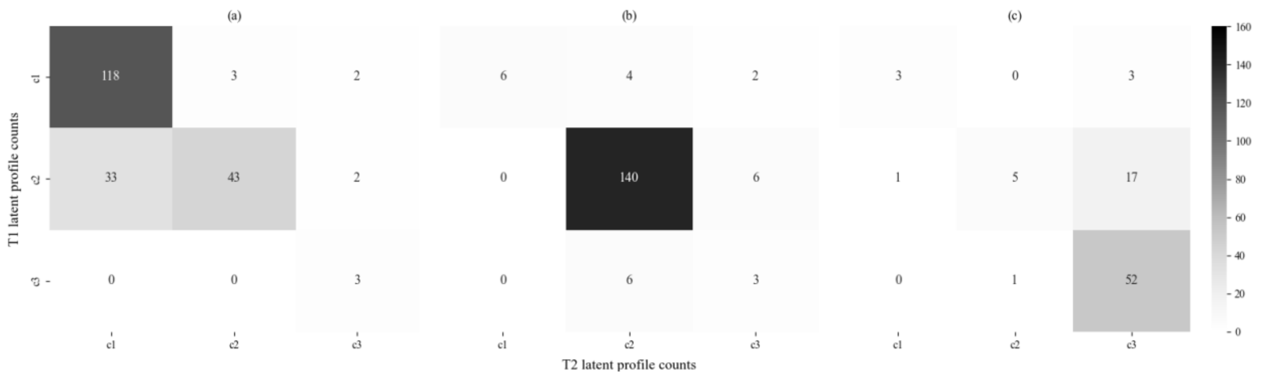
Fig. 1 The estimated probability of negative emotional symptoms, IA and their comorbidity by latent classes at each data collection

Note. The y-axis indicates the item probability of suffering from negative emotional symptoms, IA and their comorbidity at each time point, while the x-axis shows all the items of negative emotional symptoms and IA. D= depression; A= anxiety; IA= Internet addiction.



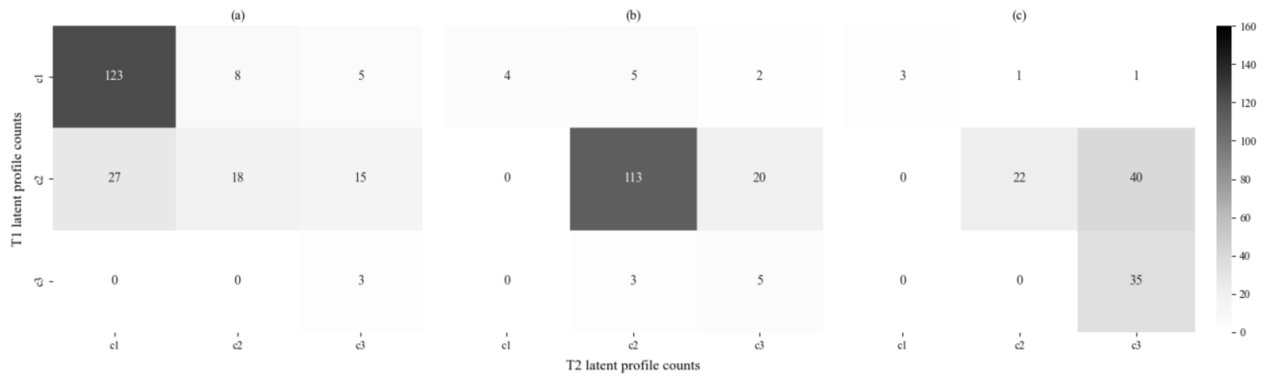
(1) The class counts of latent class pattern for negative emotional symptoms over time

c1: low negative emotional symptoms; c2: moderate negative emotional symptoms; c3: high negative emotional symptoms.



(2) The class counts of latent class pattern for IA over time

c1: low IA symptom; c2: moderate symptom; c3: high IA symptom.



(3) The class counts of latent class pattern for comorbidity over time

c1: low comorbidity symptom; c2: moderate comorbidity symptom; c3: high comorbidity symptom.

Fig. 2 The class counts of latent class patterns for IA, negative emotional symptoms, and their comorbidity across three data collections

Note. The y-axis represents T1 latent class counts, while the x-axis indicates counts of students moving to the T2 latent class. (1) Counts of participants moving to the c1 class at T3; (2) Counts of participants moving to the c2 class at T3; (3) Counts of participants moving to the c3 class at T3.

Table S1 Model fit indices of LCA for negative emotional symptoms, IA, and their comorbidity at each data collection

Model	AIC	BIC	aBIC	Entropy	LMR-LRT (*P*-value)	BLRT (*P*-value)
Negative emotional symptoms at T1 (baseline)						
1-class	6927.563	6985.123	6940.693	-	-	-
2-class	6212.361	6331.593	6239.558	0.801	<0.001	<0.001
3-class	**6111.862**	**6292.766**	**6153.127**	**0.782**	**0.022**	**<0.001**
4-class	6082.707	6325.283	6138.039	0.793	0.121	<0.001
Negative emotional symptoms at T2 (6-month follow-up)						
1-class	7965.245	8030.993	7980.215	-	-	-
2-class	5966.418	6102.023	5997.294	0.933	<0.001	<0.001
3-class	**5622.599**	**5828.062**	**5669.381**	**0.900**	**<0.001**	**<0.001**
4-class	5588.125	5863.445	5650.812	0.882	0.100	<0.001
Negative emotional symptoms at T3 (12-month follow-up)						
1-class	7618.085	7675.676	7631.246	-	-	-
2-class	5539.772	5659.069	5567.034	0.952	<0.001	<0.001
3-class	**5215.323**	**5396.325**	**5256.685**	**0.922**	**0.004**	**<0.001**
4-class	5151.609	5394.316	5207.072	0.846	0.263	<0.001
IA at T1 (baseline)						
1-class	3966.502	3999.376	3973.987	-	-	-
2-class	3579.874	3649.731	3595.780	0.727	<0.001	<0.001
3-class	**3521.763**	**3628.604**	**3546.089**	**0.705**	**<0.001**	**<0.001**
4-class	3505.467	3649.291	3538.214	0.746	0.080	<0.001
IA at T2 (6-month follow-up)						
1-class	4304.348	4337.257	4311.868	-	-	-
2-class	3777.340	3847.273	3793.321	0.772	<0.001	<0.001
3-class	**3722.735**	**3829.691**	**3747.176**	**0.704**	**0.011**	**<0.001**
4-class	3714.986	3858.964	3747.887	0.734	0.209	0.040
IA at T3 (12-month follow-up)						
1-class	4140.667	4173.594	4148.205	-	-	-
2-class	3463.050	3533.020	3479.068	0.822	<0.001	<0.001
3-class	**3341.725**	**3448.738**	**3366.223**	**0.841**	**<0.001**	**<0.001**
4-class	3334.669	3478.726	3367.648	0.790	0.208	0.040
Comorbidity of negative emotional symptoms and IA at T1 (baseline)						
1-class	10894.065	10984.566	10914.746	-	-	-

2-class	9907.501	10092.617	9949.803	0.835	<0.001	<0.001
3-class	**9738.675**	**10018.4062**	**9802.598**	**0.789**	**0.048**	**<0.001**
4-class	9623.752	9998.0970	9709.295	0.786	0.295	<0.001
Comorbidity of negative emotional symptoms and IA at T2 (6-month follow-up)						
1-class	12269.593	12368.374	12292.207	-	-	-
2-class	10052.014	10253.693	10098.184	0.943	<0.001	<0.001
3-class	**9586.932**	**9891.508**	**9656.658**	**0.896**	**0.001**	**<0.001**
4-class	9455.617	9863.090	9548.899	0.876	0.368	<0.001
Comorbidity of negative emotional symptoms and IA at T3 (12-month follow-up)						
1-class	11758.752	11849.302	11779.481	-	-	-
2-class	9435.820	9621.035	9478.221	0.944	<0.001	<0.001
3-class	**9027.790**	**9307.671**	**9091.863**	**0.894**	**0.003**	**<0.001**
4-class	8776.622	9151.168	8862.366	0.907	0.001	<0.001

Note. Akaike Information Criterion (AIC); Bayesian Information Criterion (BIC); adjusted BIC (aBIC); Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT); Bootstrapped Likelihood Ratio Test (BLRT). The bold values represent the final model at T1, T2 and T3, respectively.