Distinct Patterns of Problematic Smartphone Use: A Latent Profile Analysis Among Chinese College Students

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Abstract

Background: This study aimed to categorize different subgroups of problematic smartphone use among Chinese college students. Differences in gender and psychosocial characteristics of the categorized groups were also examined.

Methods: A total of 1,123 participants completed the Mobile Phone Addiction Index Scale (MPAI), the Center for Epidemiologic Studies Depression Scale (CES-D), the Perceived Social Support Scale, and the Perceived Stress Scale. Using latent profile analysis (LPA), we identified different subgroups of problematic smartphone use among college students. Multivariate logistic regression analysis was implemented to examine the relationship between latent classes and demographic, psychosocial covariates.

Results: Four latent classes were identified: a low-risk group, a moderate-risk with no evasiveness group, a moderate-risk with evasiveness group, and high-risk group that accounted for 11.0%, 24.1%, 35.5%, and 29.4% of the total sample, respectively. Further analysis revealed that compared with the “low-risk” class, the other three classes differed significantly with respect to gender and prevalence of depression.

Conclusions: Classifying college students based on features of problematic smartphone use is potentially useful for understanding risk factors and developing targeted prevention and intervention programs.

Introduction

Smartphones gained widespread popularity in 2011, and they have experienced an increase in usage over the past decade, especially in Mainland China. In August 2021, the China Internet Network Information Center reported that 10.07 billion Chinese people own a personal mobile phone that has internet access and that up to 99.6% of them use their smartphone to surf the internet [1]. Because smartphones have permanent access to the internet and can meet a range of demands, users have become extraordinarily attached to these devices. This trend has triggered concern about smartphone overuse among both researchers and members of the general public [2–4].

Studies reported that 6.3% of teenagers (6.1% among boys and 6.5% among girls) show signs of problematic smartphone use (PSU) [5], and another study estimated that the prevalence of PSU amongst undergraduates in China was 21.3% in 2015 [6]. A review also concluded that children and young people’s rate of PSU fell between 10% and 30% from 2011-2017 and that the median is close to 25% [7]. Given that PSU is a recent phenomenon, research centered on this problem is still emerging, and further empirical studies are needed to support and enrich these critical conversations [3].

Similar to behavioral addictions, such as gambling disorder and internet gaming disorder, excessive smartphone is associated with a series of adverse effects [8], such as problems related to physical health and cognition (e.g., poor sleep, poor memory, and decline in self-control) [7, 9], emotional problems (e.g., depression and anxiety) [4, 10], and social issues (e.g., impaired family and school relationships) [11]. Despite these negative effects, however, the proposal to make mobile phone addiction a new category in the DSM-5 was rejected [12] due to academic debates about whether or not people can become addicted to smartphone use [7]. In some cases, extreme problematic use of smartphones includes heavy gaming, which can be classified as a separate type of digital addiction [9].

Previous literature views smartphones as physical objects akin to “the glass in alcohol addiction” or “the needle in heroin addiction” and thus believes that we should not ascribe the problems that stem from smartphone usage to the device itself [3]. In other words, because of the platform and interface of smartphones, problematic smartphone
use overlaps with but is also distinct from the constructs of addiction [2, 10]. In order to build on this critical conversation, the current study adopted the concept of “Problematic Smartphone Use (PSU)” and defines it as a maladaptive mobile phone use pattern where people cannot be separated from their smartphone or control how much they use it, which eventually damages their physical and mental health and hinders their daily functions [3, 5, 7].

The classification of PSU has been inconsistent in previous studies. One method of classification identified two types of PSU (“yes” and “no”) by setting clear boundaries [13]. The most common approach has been to divide PSU into three categories using “mean ± standard deviation (SD),” in which “problematic use group” usually refers to instances where an individual’s score is neither “above mean + 1SD” nor “below mean - 1SD” [14]. This variable-oriented method does not reveal different patterns among individuals, however, and may lead to overly generalized conclusions based on the sample [15]. However, a person-oriented method captures information at the individual level and can distinguish meaningful patterns of characteristics in molecular groups [16]. In recent years, person-oriented research methods, such as latent class analysis (LCA), have become more popular in the study of disease heterogeneity [17]. Latent profile analysis (LPA) is a form of LCA that is used for the assessment of continuous indicators and is an empirically derived approach for revealing unobserved heterogeneity in a population to identify different categories of participants within a given sample [18]. Studies have shown that this probability-based and individual-centered approach could reduce the rate of misclassification and missingness among participants [19]. Given that LPA is considered the best method to diagnose class heterogeneity when no clinical interview is available [20, 21], the current study used this approach to explore specific patterns of PSU in college students.

A small body of research has attempted to identify typologies of PSU using a LCA [22, 23]. Different studies have varied in the number of subgroups that they report, describing anywhere from three to six separate subgroups. Most of the existing studies focused on small sample sizes. Potential category characteristics and their influencing factors should thus be explored in more depth using larger sample data. Several predictors attributable to high-symptom-level subgroups have been identified. For example, with respect to gender, most studies concluded that women are more likely to exhibit PSU than men; however, these findings are controversial, and a deeper investigation into variability across samples is still needed. In addition, influencing factors such as age [24, 25], low self-esteem [26, 27], loneliness [28], stress [29], affective disorders [30], personality [31], and social networks intensity [32] were reported. Studies of adolescents and adults have identified psychopathological factors associated with PSU. In this type of research, anxiety and depression have been the main focus [33]. In summary, the current study performed LPA to identify unobserved and homogeneous subtypes of PSU in college students and then explored the relationship between these potential types and demographic and psychosocial factors.

**Method**

**Participants and procedures**

Data was acquired from a large cross-sectional project. All participants were recruited in December 2018 at Wenzhou Medical University in Wenzhou City, Zhejiang Province, China. The inclusion criteria for the study were as follows: 1) willingness to participate in the baseline and 2) daily smartphone use. Date was collected from undergraduate students enrolled in a range of medical majors, including psychiatry, clinical medicine, and traditional Chinese medicine. A total of 1,150 subjects completed the survey anonymously. Twenty-seven (2.3%) were excluded because more than 20% of the data was missing on one or more scales of key psychological variables. Thus, the final study sample consisted of 1,123 (97.7%) participants.
Measures

Self-report demographic survey

While under the supervision of trained evaluators, the participants filled in the social and demographic section of the survey. This section collected general information from the participants, such as gender, grade, residence, and single child status.

Mobile Phone Addiction

The Mobile Phone Addiction Index Scale (MPAI) was used to quantitatively assess the participants’ mobile phone use levels [34]. The scale assesses four dimensions: inability to control cravings, feeling anxious and lost, withdrawal or escape, and loss of productivity [35]. The scale includes 17 items, which are rated on a 5-point Likert scale. The higher the score, the more addicted the participants are to their mobile phones. The Cronbach's alpha in this study was 0.82.

Depression

The Center for Epidemiologic Studies Depression Scale (CES-D) [36] was used to assess the participants’ depression status. The scale comprises 20 items, each of which are scored according to the severity of symptoms, and assesses nine symptoms of depression [37]. The higher the score, the more severe the symptoms of depression. The CES-D is one of the most widely used self-report scales because it has good psychometric properties that allow for the assessment of depressive symptoms in the general public [36]. The Cronbach's alpha in this study was 0.86.

Perceived Social Support

The 12-item Perceived Social Support Scale was used for measuring the participants’ levels of perceived social support [38, 39]. The scale assesses three dimensions: family support, friend support, and other forms of support (e.g., teachers and relatives). The scale has good reliability and validity in Chinese populations [40]. The higher the score, the more social support available to the participant. The Cronbach's α was 0.86.

Perceived Stress

The Perceived Stress Scale [41] was used to measure the extent to which respondents felt that their stress was unpredictable, uncontrollable, and overwhelming. It consists of 14 entries allowing 5-Likert scale responses: never (0) to frequently (4). Total scores ranged from 0 to 56, with higher scores indicating greater perceived stress. The Cronbach's α for the current sample was 0.73.

Statistical analysis

Identification of potential categories
M-plus version 8.0 [42] was used to construct a LPA so that any heterogeneous latent category differences in the PSU could be characterized. LPA provides classification of individuals and is a special case of finite mixture modeling. Unlike other approaches, such as cluster analysis, cases are not absolutely assigned to but have a certain probability of belonging to a class [43]. The evaluation indicators of the degree of fit of an LPA are the Akaike Information Criterion (AIC) [44], Bayesian Information Criterion (BIC) [45], and sample-size adjusted BIC (aBIC) [46]. This is a relative metric where lower values of BIC, AIC, and aBIC are better. The second is the entropy value, with a maximum value of 1 and high values preferred [47]. An entropy value greater than 0.8 indicates a classification accuracy of over 90% [48]. Priority was given to entropy in cases where fit indices between the two models were relatively similar. The bootstrapped likelihood ratio test (BLRT) and Lo-Mendell-Rubin test (LMR) were also considered. A significant likelihood ratio test for k classes with \( p < 0.05 \) indicates that the specified k-class model is an improvement over a model with k-1 classes [49]. To avoid solutions based on local maxima, we used 200 random sets of starting values initially and 50 final stage optimizations. Additionally, each latent class was defined with meaningful clinical interpretability [50]. Posterior probabilities from the model were used to assign each participant to their most likely class [17].

**Identification Of Risk Factors**

Instead of deleting missing values, this study replaced them with average values. All categorical variables were described as counts and percentages, and all continuous variables were described as means and standard deviations. Using the classification results of the potential categories as dependent variables and the demographic factors, rates of depression, perceived social support, and perceived stress scores as independent variables, a multinomial logistic regression model was then established using SPSS version 22.0. Odds ratios (OR) with 95% confidence intervals are reported with a significance level set at 5%.

**Results**

**Characteristics of the participants**

A total of 1,123 college students participated in this study. Descriptive statistics for the sample are presented in Table 1. Seven hundred and four participants (62.6%) were female, and 419 (37.4%) were male. The majority lived in the city (n= 636, 56.6%), and 592 (52.7%) were not an only child. The overall mean CES-D score was 36.0 (SD=9.3).

**Latent profile analysis**

Following a person-centered approach, LPA was used to identify PSU among college students in this study. Five latent class models were estimated, and the fit indices of the generated models are reported in Table 2. The AIC, BIC, and aBIC continuously decreased as the number of latent classes increased. The LMR value of the five class solutions was not statistically significant \((p > 0.05)\). Compared to the two- and three-class solution, the AIC, BIC, and aBIC values indicated that the four-class solution was preferable, as did the entropy value. The high posterior probabilities of memberships of the four latent classes (0.943, 0.889, 0.914, and 0.936, respectively) also indicate good discrimination. The four-class solution was thus selected as the optimal solution.

Our results revealed a four classes solution that was hierarchically organized, meaning the classes varied from the highest to the lowest frequencies of symptom endorsement. Fig. 1 depicts the profiles of PSU across...
the four classes. Class 1 was labeled as the “low-risk group” (n = 123, 11.0%) due to the fact that this subgroup received the lowest item scores on the MPAI. When compared with the “low-risk group,” Class 2 and Class 3 demonstrated more severe smartphone-related problems. Class 3 scored significantly higher on evasiveness (item 13: “when I feel isolated, I use my phone to chat with others”; item 14: “when I feel lonely, I use my phone to chat with others”; item 15: “when the mood is low, I play with the phone to improve the mood”) compared to Class 2; so, Class 3 was named the “moderate-risk with evasiveness group,” and the Class 2 was called the “moderate-risk with no evasiveness group.” Class 4 comprised approximately 29.4% of the sample (n=330). Participants in this group showed a poorer psychosocial profile with respect to their inability to control cravings, feeling anxious and lost, withdrawal or escape, and productivity loss. Individuals in Class 4 were the most likely to experience all the different forms of PSU. This class was labeled the “high-risk group.”

Predicting class membership

Using the “low-risk group” as the reference class, the multinomial regression analysis results are shown in Table 3. First of all, in terms of gender, there were significant differences between classes. Females were more likely to exhibit PSU than males. Females were 1.96 (95% CI: 1.27-3.00) and 2.23 times (95% CI: 1.43-3.46) more likely to belong to the “moderate-risk with evasiveness group” and “high-risk group.” Additionally, individuals in the ‘moderate risk with no evasiveness group’ were significantly more likely to have a depressed mood (OR = 1.08, 95%CI: 1.05-1.11). Depression also increased the odds of participants falling into Class 3 (OR = 1.04, 95%CI: 1.02-1.07) and Class 4 (OR = 1.11, 95%CI: 1.08-1.15).

Discussion

Past research on PSU has demonstrated identified a heterogeneous and hierarchical organization by identifying classes of individuals based on their symptoms [22, 23]. Our study demonstrated a similar heterogeneous and hierarchical organization of PSU in a sample of Chinese college students. Results from the LPA supported a four-class model sorted by frequency of symptoms: (a) the low-risk group, (b) the moderate-risk with no evasiveness group, (c) the moderate-risk with evasiveness group, and (d) the high-risk group. This classification not only supported the hierarchical nature of PSU in college students but also revealed differences in PSU types across categories, reflecting heterogeneity between categories.

The subgroup of adolescents that displayed low frequencies on all PSU symptoms was labeled the “low-risk group.” This subgroup accounted for the lowest proportion of participants (n=123, 11.0%). The percentage of participants in the “high-risk group” class included 29.4% (n=330) of the individuals in our total sample. Though most studies report that the low-risk group is larger than the high-risk group, this is not consistent with our findings. These discrepancies could be due to the different instruments used and also differences among the participants in the various studies. Additionally, research on factors related to the culture of internet addiction has concluded that internet addiction is linked with rapid national development. This is because a country’s development is tied to advances in new media and technology in many aspects of life, which can lead to excessive internet use [51]. Thus, our study reveals the diversity of PSU and shows how its prevalence varies across regions.

The percentage of students in the “moderate-risk group” (n = 670, 59.6%) was the highest among the four classes. This is consistent with the results of previous studies [31, 52]. The medium-risk group is divided into two groups, the “moderate-risk with no evasiveness group” and the “moderate-risk with evasiveness group.” Class 3 scored higher on the evasiveness dimension compared to Class 2, which is a result rarely seen in previous studies. The
results of the internet questionnaire revealed that lonely and anxious individuals have different smartphone usage patterns. Lonely people preferred to make voice calls and rated texting as a less intimate method of contact, while anxious people preferred texting and rated it as the superior medium for expressive and intimate contact [53]. Studies have also shown that PSU and loneliness show a significant positive correlation and that loneliness is a major predictor of addiction to social networking services [54]. Similarly, PSU was associated with trait anxiety [10, 30]. Based on these findings, we can speculate that the third group of students had higher levels of loneliness and anxiety, which requires further research to prove.

In addition to exploring the heterogeneous and hierarchical organization of PSU, this study found significant variations between gender and depression levels among the four latent classes. The results of multinomial logistic regression analyses revealed significant gender differences among the classes. The relationship between PSU and gender was investigated in some studies where females’ average overuse of mobile phones was shown to be higher than males. However, in other studies, gender had no significant relationship with mobile phone overuse [55–57]. Geser argued that the motivations and goals of smartphone usage mirror conventional gender roles (p.3) [58]. Females tend to view smartphones and the internet as communication tools that they can use to maintain and nurture relationships, while males typically view them as a source of entertainment and information [59]. For example, females use social networking sites mainly to communicate with their peers [60], and they are more concerned with social usability, whereas males use smartphones more often for leisure and interest [61, 62]. Consequently, men are more likely to become addicted to online video gaming, cyber-pornography, and online gambling [63]. Moreover, females show higher levels of attachment to and dependence on smartphones [64, 65]. Surveys show that females aged 20 or older are three times more likely than males (25% vs. 9%) to agree with the statement, “I can’t imagine my life without the phone” [58]. Considering the results of the current study, it is clear that males and females use their smartphones for different purposes, which ultimately leads to different patterns of smartphones use. The “social factor” hypothesis argues that females are exposed to more stressful life events and are thus more vulnerable than males. Compared to men, women have a greater tendency to “internalize” or be more passive and less “mentally tough,” so they have a stronger tendency to develop anxiety or depression, which can lead to problems such as PSU [63].

Depression severity was significantly associated with PSU, which is consistent with the findings of previous studies [10]. Recent research shows that PSU severity was moderately correlated with anxiety and depression severity [26, 66, 67] and that this association could extend to adults of all ages [68]. PSU and depression interrelationships found in prospective cohort studies are likely to be significantly bi-directional [69, 70]. On the one hand, PSU is associated with a lack of social support, which can induce emotional disorders such as anxiety and depression [71]. Smartphone overuse and tolerance could cause people to use their smartphones for long periods of time at night, which can lead to sleep problems that could lead to anxiety and depression [72]. On the other hand, PSU has an impact on neural activity by affecting rewording progress [73]. Phone use usually offers rewards to people and therefore ensures that behavior will reoccur [74]. As a result of this newly established reward mechanism, when an individual puts down their mobile phone and returns to daily life, satisfaction is not as easy or quick to attain, which can lead to dissatisfaction and depression.

Additionally, individuals with depressive moods are more vulnerable to PSU. Compensatory internet use theory (CIUT) suggests that people with negative emotions may alleviate bad moods through excessive smartphone use, so people with depression may be more susceptible to PSU than psychologically healthy people [75]. Current research views PSU as a coping mechanism to eliminate negative emotions, trigger positive feelings, and compensate for a lack of offline socialization [76]. People with depression are likely to overuse their smartphones
to compensate for negative emotions, such as sadness and despair. This is because using a smartphone can bring pleasant experiences and offer a temporary escape from a depressing reality.

However, studies have also found that college students who reported major depressive symptoms were less likely to use smartphones for social purposes [77]. Process and social motivation have been found to be associated with smartphone use/problem use. Process motive refers to the consumption of media for entertainment seeking and escapism [78], and social motive is linked to the use of media to communicate and build relationships with others [74]. People with depression are socially withdrawn and isolated [79], perceive themselves as incompetent, and tend to interact with others in a way that leads to rejection, which inhibits their participation in interpersonal relationships [79]. Due to social withdrawal, these individuals are rarely motivated to and even sometimes avoid interacting with others [80]. Therefore, the use of smartphones by depressed patients to compensate for their negative emotions (e.g., sadness and despair) is linked to process motive. Playing with smartphones for entertainment or escapism could be an enjoyable experience or distract users from reality [81]. This suggests that future studies should distinguish between the different motivations for PSU.

**Limitations**

This study has several limitations. First, the data was only collected from one university, which may limit the generalizability of these findings. Future research should examine PSU with a sample that is more representative of the general population. Second, the participants were all medical students who did not exhibit significant functional impairments. Future studies should expand to the clinical setting, and it is also recommended that the results gathered from the clinical population be compared with the findings from this study. Third, the use of neurocognitive tests or neurobiological markers would increase the validity of the results [31].

**Conclusion**

This study has identified four trajectories of PSU and the factors associated with each group. The results demonstrated that being female and exhibiting symptoms of depression are risk factors. As an extension of this research, it may be possible to achieve early identification of college students at high risk of PSU. In order to improve PSU, more attention should be paid to individuals with risk factors, namely female college students with depression.

**Abbreviations**

PSU: problematic smartphone use; LCA: latent class analysis; LPA: Latent profile analysis; AIC: Akaike information criterion; BIC: Bayesian information criterion; aBIC: adjust Bayesian information criterion; BLRT: Bootstrap likelihood ratio test; LMR: Lo-Mendell-Rubin test; CI: confidence interval; OR: odds ratio. CES-D: Center for Epidemiologic Studies Depression Scale; PSSS: Perceived Social Support Scale; PSS: Perceived Stress Scale.

**Declarations**

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**Authors’ contributions**
Authors GZ, KZ, DX and XY designed the study and wrote the protocol. Authors LH, XL conducted the statistical analysis. Authors LH, XL, WZ, BW conducted literature searches and wrote the first draft. Authors GZ, KZ, LH reviewed and edited the manuscript. All authors contributed to and have approved the final manuscript.

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**Availability of data and materials**

The data is available on request from the Department of Psychology, Wenzhou Medical University (see Additional file 1). Guohua Zhang had received permission and accessed to all the data.

**Ethics approval and consent to participate**

The study procedures were carried out in accordance with the Declaration of Helsinki. At the beginning of the research, the researchers explain the project to the participants. The information included the aims of the study, principle of privacy and confidentiality, declaration of voluntary participation and contact information of the researcher. Potential participants were also informed that they could withdraw at any time. All subjects all provided informed consent. The study protocol was reviewed and approved by the Research Ethics Committee, Wenzhou Medical University before the research was carried out.

**Consent for publication**

Not applicable.

**Competing interests**

The authors declare that there are no conflict interests.

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Table 1. Demographic characteristics of the sample.

| Characteristics     | Total (n = 1123) |   |
|---------------------|------------------|---|
|                     | n / Mean | % / SD |
| Gender              |          |      |
| Female              | 704      | 62.6  |
| Male                | 419      | 37.4  |
| Grade               |          |      |
| Freshman            | 346      | 30.8  |
| Sophomore           | 414      | 36.9  |
| Junior              | 363      | 32.3  |
| Family Origin       |          |      |
| City                | 636      | 56.6  |
| Rural               | 487      | 43.4  |
| One-child family    |          |      |
| Yes                 | 531      | 47.3  |
| No                  | 592      | 52.7  |
| CES-D               | 36.0     | 9.3   |
| PSSS                | 61.5     | 14.4  |
| PSS                 | 39.3     | 6.4   |
| MPAI                | 48.5     | 10.8  |

Note: SD=standard deviation, CES-D: Center for Epidemiologic Studies Depression Scale, PSSS: Perceived Social Support Scale, PSS: Perceived Stress Scale, MPAI: Mobile Phone Addiction Index Scale.

Table 2. Model fit indices for one- to five-profile pattern of MPAI items and profile prevalence (%) of LPA (n = 1123).
| No. of classes | AIC       | BIC       | aBIC      | Entropy | LMR     | BLRT     | Proportion of individuals in Category |
|---------------|-----------|-----------|-----------|---------|---------|----------|---------------------------------------|
| 1             | 60560.119 | 60730.927 | 60622.933 | —       | —       | —        | —                                    |
| 2             | 58054.385 | 58315.621 | 58150.454 | 0.812   | <0.001  | <0.001   | 47.1/52.9                             |
| 3             | 57288.773 | 57640.436 | 57418.097 | 0.843   | <0.05   | <0.001   | 12.2/55.7/32.0                        |
| 4             | 56707.082 | 57149.173 | 56869.661 | 0.849   | <0.05   | <0.001   | 11.0/24.1/35.5/29.4                   |
| 5             | 56397.232 | 56929.750 | 56593.065 | 0.821   | >0.05   | <0.001   | 10.4/22.5/23.3/20.0/23.7              |

*Note:* Abbreviations: The values reported in this table are hypothetically derived for illustrative purposes. AIC = Akaike information criterion; BIC = Bayesian information criterion; aBIC = adjust Bayesian information criterion; BLRT = bootstrap likelihood ratio test; LMR = Lo-Mendell-Rubin test; Bold indicates the selected category.

Table 3. Predictors of the latent group membership for the PSU based on the multinomial regression.
| Variables          | moderate risk with no evasiveness group (n=271, 24.1%) | moderate risk with evasiveness group (n=399, 35.5%) | high risk group (n=330, 29.4%) |
|-------------------|------------------------------------------------------|-----------------------------------------------------|-----------------------------|
|                   | OR         | 95% CI | p       | OR         | 95% CI | p       | OR         | 95% CI | p       |
| Gender            | 1.24       | 0.79-1.94 | 0.347 | 1.96       | 1.27-3.00 | 0.002 | 2.23       | 1.43-3.46 | 0.000 |
| Female            | ref        | 0.44-1.37 | 0.383 | 0.85       | 0.49-1.46 | 0.553 | 0.85       | 0.49-1.47 | 0.551 |
| Male              |            | 0.43-1.20 | 0.206 | 0.81       | 0.50-1.34 | 0.206 | 0.63       | 0.38-1.05 | 0.076 |
| Grade             | 0.72       | 0.60-1.52 | 0.844 | 0.75       | 0.48-1.17 | 0.205 | 0.89       | 0.56-1.40 | 0.603 |
| Freshman          | ref        | 0.96     | 1.06    | 0.817      | 1.49     | 0.084 | 1.28       | 0.81-2.04 | 0.288 |
| Sophomore         |            | 1.08     | 1.05-1.11 | 0.00 | 1.04     | 1.02-1.07 | 0.003 | 1.11     | 1.08-1.15 | 0.000 |
| Junior            |            | 0.98     | 0.96-1.02 | 0.50 | 0.99     | 0.97-1.03 | 0.83 | 0.98     | 0.95-1.02 | 0.400 |
| Family Origin     | 1.11       | 1.01     | 0.93-1.09 | 0.85 | 1.02     | 0.94-1.09 | 0.68 | 0.99     | 0.91-1.08 | 0.820 |
| Rural             |            | 1.01     | 0.96-1.02 | 0.50 | 0.99     | 0.97-1.03 | 0.83 | 0.98     | 0.95-1.02 | 0.400 |
| City              |            | 0.98     | 0.96-1.02 | 0.50 | 0.99     | 0.97-1.03 | 0.83 | 0.98     | 0.95-1.02 | 0.400 |
| Single child      | 1.11       | 1.01     | 0.93-1.09 | 0.85 | 1.02     | 0.94-1.09 | 0.68 | 0.99     | 0.91-1.08 | 0.820 |

Note: The reference category is “low risk group”. CI: confidence interval; OR: odds ratio. CES-D: Center for Epidemiologic Studies Depression Scale; PSSS: Perceived Social Support Scale; PSS: Perceived Stress Scale.

Figures
Figure 1

Profiles for 4-class LPA model of PSU.

Supplementary Files

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- Additionalfile1.xls