Classification of probable online social networking addiction: A latent profile analysis from a large-scale survey among Chinese adolescents

JI-BIN LI1,2,3*, ANISE M.S. WU4, LI-FEN FENG5, YANG DENG6, JING-HUA LI6, YU-XIA CHEN7, JIN-CHEN MAI7, PHOENIX K.H. MO3** and JOSEPH T.F. LAU3***

1 Department of Clinical Research, Sun Yat-sen University Cancer Center, Guangzhou, 510060, P.R. China
2 State Key Laboratory of Oncology in South China, Collaborative Innovation Center for Cancer Medicine, Guangzhou 510060, P. R. China
3 Center for Health Behaviours Research, The Jockey Club School of Public Health and Primary Care, The Chinese University of Hong Kong, Hong Kong, P.R. China
4 Department of Psychology, Faculty of Social Sciences, University of Macau, Taipa, Macao, P.R. China
5 Department of Statistics, Government Affairs Service Center of Health Commission of Guangdong Province, Guangzhou, 510060, P.R. China
6 School of Public Health, Sun Yat-sen University, Guangzhou, 510080, P.R. China
7 Department of Psychological Health Research, Center for Health Promotion of Primary and Secondary School of Guangzhou, Guangzhou, P.R. China

Received: January 02, 2020  •  Revised manuscript received: May 06, 2020; July 01, 2020  •  Accepted: July 06, 2020

ABSTRACT

Background and aims: Problematic online social networking use is prevalent among adolescents, but consensus about the instruments and their optimal cut-off points is lacking. This study derived an optimal cut-off point for the validated Online Social Networking Addiction (OSNA) scale to identify probable OSNA cases among Chinese adolescents. Methods: A survey recruited 4,951 adolescent online social networking users. Latent profile analysis (LPA) and receiver operating characteristic curve (ROC) analyses were applied to the validated 8-item OSNA scale to determine its optimal cut-off point. Results: The 3-class model was selected by multiple criteria, and validated in a randomly split-half subsample. Accordingly, participants were categorized into the low risk (36.4%), average risk (50.4%), and high risk (13.2%) groups. The highest risk group was regarded as "cases" and the rest as "non-cases", serving as the reference standard in ROC analysis, which identified an optimal cut-off point of 23 (sensitivity: 97.2%, specificity: 95.2%). The cut-off point was used to classify participants into positive (probable case: 17.0%) and negative groups according to their OSNA scores. The positive group (probable cases) reported significantly longer duration and higher intensity of online social networking use, and higher prevalence of Internet addiction than the negative group. Conclusions: The classification strategy and results are potentially useful for future research that measure problematic online social networking use and its impact on health among adolescents. The approach can facilitate research that requires cut-off points of screening tools but gold standards are unavailable.

KEYWORDS

online social networking addiction, classification, latent profile analysis, adolescents
INTRODUCTION

Online social networking has become very popular and affects all aspects of adolescents’ daily lives (Pantic, 2014). Over 70% of the American teenagers were social media users in 2012 (Bull, Levine, Black, Schmiege, & Santelli, 2012), and 38% and 77% of the European adolescents aged 9–12 and 13–16 years had online social networking accounts in 2011, respectively (Livingstone, Haddon, Görzig, & Olafsson, 2011). Among adolescents in mainland China (Shi & Niu, 2010) and Belgium (De Cock et al., 2014), 12% and 6.55% spent >1 hour per day and >16 hours per week on online social networking, respectively. A previous study shows that college students in mainland China reported a higher prevalence of problematic online social networking use (44.9%) compared to their counterparts in other regions (the U.S., Singapore, Hong Kong/Macau, South Korea, and Japan) (Tang et al., 2018). Problematic online social networking use causes significant harms to mental health and well-being among adolescents (Andreassen, 2015; Ryan, Chester, Reece, & Xenos, 2014). Online social networking provides an important medium for social interaction for adolescents. Compared with offline face-to-face interactions, it has the advantages of anonymity, flexibility of selective self-disclosure, and no constrains of geography and time. Such features may lead to addictive behaviors (Byun et al., 2009; Kornas, Critselis, Janikian, Kafetzis, & Tsitsika, 2011).

As online social networking addiction (OSNA) is not part of International Classification of Diseases (11th edition), problematic online social networking use is not officially recognized as an addiction. Some researchers have used the term disordered online social networking use to describe the problem (e.g., Hormes, Kearns, & Timko, 2014). However, OSNA remains a commonly used term (e.g., Echeburua & De Corral, 2010; Griffiths, 2013; Griths, Kuss, & Demetrovics, 2014), with consideration that people with disordered online social networking tend to exhibit core addictive symptoms that are similar to those of other behavioral addictions, such as cognitive and behavioral salience, conflict with other activities, euphoria, loss of control, withdrawal, relapse, and reinstatement (Griffiths, 2005). Given such background and the consideration that the objective of this study was to derive a cut-off point for the OSNA scale, the term OSNA was used in this report. Cautiously, it is noteworthy that the term “probable OSNA cases” refers to the group that was positively screened by the OSNA scale (i.e., those who scored above the cut-off point); they are those having higher risk of having problematic online social networking use and its potential harms, instead of having higher risk of having an addictive disorder. Similar to our case, those who scored above the cut-off point of other screening tools (e.g., CES-D) have also been known as “probable cases” (e.g., Brar et al., 2020).

Cut-off points of screening tools are important in epidemiological research and identification of individuals who need interventions. Few studies have examined cut-off points of OSNA assessment tools. In general, clinical interviews are used as the gold standard for evaluating scale performance and selection of cut-off points of assessment tools. An example was the derivation of the cut-off point for the Chen Internet Addiction Scale (Ko et al., 2009). In the absence of clinical interviews, some epidemiological approaches have been developed and used to select cut-off points. The latent profile analysis (LPA) is one such method. It has been used to derive the cut-off points for the 6-item Bergen Social Media Addiction Scale (Banyai et al., 2017), the 10-Item Internet Gaming Disorder Test (Kiraly et al., 2017), and the public awareness questionnaire of type 2 diabetes (Shirmohammadi, Soltanian, & Borzouei, 2018).

LPA classifies individuals who give similar responses to a set of observed variables into a latent class. As all items of an assessment tool contribute to the overall symptom level of a health problem, a latent class identified by LPA include people with similar severity of the disorder. To determine the cut-off point of an assessment tool, the latent class that represents the most severe level of disorder is regarded as the “case” group, while the other participants belong to the “non-case” group. The two groups are then used as the reference standard to derive sensitivities and specificities for potential cut-off points (Kiraly et al., 2017). The reference standard is not a gold standard, which is unavailable for OSNA; the method has been applied to identify cut-off points that can be used for practical purposes in the absence of gold standards (Garrett, Eaton, & Zeger, 2002; van Smeden, Naaktgeboren, Reitsma, Moons, & de Groot, 2014). Using the reference standard derived from LPA, the receiver operating characteristic curve (ROC) method is then applied to select an optimal cut-off point and examine its statistical performance.

The present study applied the LPA and ROC methods to derive a cut-off point for the OSNA scale. To establish external validity, we tested the associations between the classification outcomes (i.e., positive and negative groups), LPA latent classes and some external variables (e.g., frequency and intensity of online social networking use). The approach can improve applications of the OSNA scale, and can be applied to other tools that assess problematic Internet use. It supplements the identification of cut-off points based on clinical diagnosis (the gold standard), which is warranted in future studies.

METHODS

Participants and procedures

The present study used the baseline data of a 9-month longitudinal survey conducted in Guangzhou of South China, which has a population size of 14.9 million registered residents (2018). The study procedure has been described previously (Li et al., 2018). The stratified cluster sampling method was used: nine public secondary schools were selected, three from each of the three regions (i.e., core, suburb, and outer suburb regions). Of the nine selected
schools, all students of the 7th and 8th grade (i.e., students with seven and eight years of formal education, respectively) were invited to fill out an anonymous and self-administered questionnaire. The survey was briefed and conducted by well-trained field workers in classroom settings and in the absence of teachers. Information about the study’s background and the confidentiality of the study was printed on the cover page of the questionnaire. Voluntary participation was emphasized in an announcement. No incentive was given to the participants, who were clearly informed that the return of a completed questionnaire implied provision of informed consent for their participation. Of the 5,472 students invited to join the study, 5,365 students (response rate = 98.0%) completed the questionnaires; 4,951 of them (92.3%) were online social networking users; their data were analyzed in this report.

**Measures**

**Background variables:** All participants were asked about their gender, grade, parental education levels, family financial status, living arrangement with parents, self-reported academic performance, and perceived academic pressure.

**Online social networking addiction:** The OSNA was assessed using an adapted version from the Facebook Addiction Scale (Koc & Gulyagci, 2013). The Chinese version has been used in previous studies (Li et al., 2016, 2018). The OSNA scale includes eight items that measure core addictive symptoms, including cognitive and behavioral salience, conflict with other activities, euphoria, loss of control, withdrawal, and relapse and reinstatement (Griffiths, 2005). The psychometric properties have been reported previously (Cronbach’s α = 0.86) (Li et al., 2016). A 5-point Likert scale from 1 (not true) to 5 (extremely true) was used, and a higher score indicates a higher level of addictive tendency to online social networking. In the present study, the one-factor solution of OSNA was confirmed by confirmatory factor analysis, with an acceptable model fit ($\chi^2 = 448.7 (P < 0.001), $ $CFI = 0.97$, and $RMSEA = 0.074 (90\% CI: 0.068, 0.080)$), and the Cronbach’s $\alpha$ of the scale was 0.87 in the present study.

**Online social networking use intensity:** Online social networking use intensity was measured by the 14-item Online Social Networking Activity Intensity Scale (OSNAIS), which was validated among Chinese adolescents (Li et al., 2016). This scale measures social function use intensity (SFUI, 10 items) and entertainment function use intensity (EFUI, 4 items), with five-point responses from 0 (never) to 4 (always). The score range is from 0 to 40 for SFUI and from 0 to 16 for EFUI, with higher scores indicating higher intensity of online social networking use. In this study, the Cronbach’s $\alpha$ of SFUI and EFUI was 0.88 and 0.61, respectively.

**Other characteristics related to online social networking use:** Participants were asked whether they currently possessed any online social networking accounts, and if so, their duration of online social networking use, average number of days per week and amount of time spent on online social networking on a typical day, number of online social networking friends, and self-reported frequency of conflict with parents due to excessive online social networking use.

**Internet addiction:** Internet addiction was measured by the 8-item Young’s diagnostic questionnaire with “yes/no” response categories (Aboujaoude, 2010; Young, 1998). Participants who provided five or more “yes” answers were classified as probable cases of Internet addiction. The scale has been commonly used in the Chinese students, and showed acceptable validity and reliability (Li, Zhang, Lu, Zhang, & Wang, 2014). The Cronbach’s $\alpha$ was 0.67 in the present study. Again, Internet addiction was not included into ICD-11, but the term has been very commonly used in literature; it was hence used in this study.

**Statistical analysis**

The LPA was used to identify groups of participants (latent classes) who gave similar responses (i.e., similar levels of risk of having OSNA) to the OSNA scale items. First, multiple criteria were used to determine the number of latent classes (from one to six): 1) Multiple fit indices were examined. Lower values of the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC) and sample size adjusted BIC (ssAIC) indicate better model fit (Nylund-Gibson & Choi, 2018). Scree plots were used for visual examination (Masyn, 2013). A significant bootstrapping likelihood-ratio test (BLRT) result ($P$ value <0.05) implies that the model with $k$ classes fits better than that with $k$−1 classes; 2) Higher entropy values represent better classification accuracies (range from 0 to 1), and the values >0.8 imply high accuracies (Fonseca-Pedrero, Ortuno-Sierra, de Albeniz, Muniz, & Cohen, 2017); 3) All the latent classes identified by LPA should include at least 5% of the sample to eliminate fundamentally impractical solutions and prevent over fitting (Nagin, 2005; Wendt et al., 2019; Zhang, Zhang, Goyal, Mo, & Hong, 2018). There is no single criterion for deciding the number of latent classes, and the flow of the logic for decision was further explained in the Result section. Following a previous research strategy (Masyn, 2013), the identified latent class models were further cross-validated in two random split-samples [training sample ($n = 2,486$) and validation sample ($n = 2,465$)]. In the validation set, the model based on fixed parameters obtained from the training set was compared against that based on parameters freely derived from the validation set. Based on the selected number of latent classes, the sample was classified into groups with different risk levels of OSNA; the number of risk groups being that of latent classes.

In the second step, a recommended approach combining the LPA and ROC method was used to identify the cut-off point for the original OSNA scale (Garrett et al., 2002); it has also been applied to derive cut-off point for the Internet Gaming Disorder Scale (Kiraly et al., 2017). Probable OSNA cases (the latent class with the highest risk) versus non-cases (all other latent classes) identified by the LPA was used as
the reference standard. Sensitivity and specificity were derived for various scale scores of the original OSNA scale based on this reference standard; all pairs of sensitivity and specificity were then used to construct an ROC curve. The optimal cut-off point of the OSNA scale was determined by the Youden’s index (Akobeng, 2007). Participants were then divided into the positive (probable OSNA cases) and negative (probable non-cases) groups by comparing their OSNA scale score against the derived cut-off point.

In the third step, the differences of external characteristics (e.g., duration, frequency and intensity of online social networking use, and Internet addiction) between the latent classes, and between the OSNA positive/negative groups (as defined by the identified cut-off point) were compared by using χ² test (categorical variables), independent-sample t-test (two-group continuous variables), or one-way analysis of variance (three-group continuous variables). Spearman correlation coefficients were used to assess the effect sizes for associations between the latent classes, OSNA positive/negative groups, and the external characteristics. LPA was performed by Mplus 7.3, and all other statistical analyses were conducted by using SAS version 9.4 (SAS Institute, Cary, NC, USA). A two-sided P value <0.05 was considered statistically significant.

**Ethics**

The study procedures were carried out in accordance with the Declaration of Helsinki. School consent was obtained from the school principals prior to conduct the survey. Ethical approval was obtained from the Survey and Behavioral Research Ethics Committee of The Chinese University of Hong Kong.

**RESULTS**

**Characteristics of the participants**

The sample characteristics are presented in Table 1. Of all participants (n = 5,365), 52.8% were males; 48.3% were 7th

| Table 1. Sample characteristics | Online social networking users | P       |
|---------------------------------|--------------------------------|---------|
| **Gender**                      |                                |         |
| Male                            | 2,533 (47.2)                   | 2,394 (48.4) | <0.001 |
| Female                          | 2,832 (52.8)                   | 2,557 (51.6) |         |
| **Grade**                       |                                |         |
| Seven                           | 2,592 (48.3)                   | 2,379 (48.1) | 0.184  |
| Eight                           | 2,773 (51.7)                   | 2,572 (51.9) |         |
| **Father education level**      |                                |         |
| Primary school or below         | 356 (6.6)                      | 317 (6.4)  | 0.140  |
| Junior middle school            | 1,816 (33.9)                   | 1,683 (34.0) |         |
| Senior middle school            | 1,646 (30.7)                   | 1,529 (30.9) |         |
| University or above             | 1,317 (24.5)                   | 1,212 (24.5) |         |
| Unknown                         | 230 (4.3)                      | 210 (4.2)  |         |
| **Mother education level**      |                                |         |
| Primary school or below         | 588 (11.0)                     | 532 (10.7)  | 0.222  |
| Junior middle school            | 1,909 (35.6)                   | 1,761 (35.6) |         |
| Senior middle school            | 1,497 (27.9)                   | 1,398 (28.2) |         |
| University or above             | 1,143 (21.3)                   | 1,052 (21.2) |         |
| Unknown                         | 228 (4.3)                      | 208 (4.2)   |         |
| **Family financial status**     |                                |         |
| Very good/good                  | 2,519 (47.0)                   | 2,357 (47.6) | <0.001 |
| Average                         | 2,664 (49.6)                   | 2,441 (49.3) |         |
| Poor/very poor                  | 182 (3.4)                      | 153 (3.1)   |         |
| **Living with both parents**    |                                |         |
| Yes                             | 4,712 (87.8)                   | 4,351 (87.9) | 0.683  |
| No                              | 653 (12.2)                     | 600 (12.1)   |         |
| **Academic performance**        |                                |         |
| Upper                           | 1,817 (33.9)                   | 1,679 (33.9) | 0.193  |
| Medium                          | 2,396 (44.6)                   | 2,223 (44.9) |         |
| Lower                           | 1,152 (21.5)                   | 1,049 (21.2) |         |
| **Perceived academic pressure** |                                |         |
| Nil                             | 205 (3.8)                      | 186 (3.8)   | 0.042  |
| Light                           | 829 (15.5)                     | 753 (15.2)   |         |
| Average                         | 3,052 (56.9)                   | 2,836 (57.3) |         |
| Heavy                           | 1,001 (18.7)                   | 929 (18.8)   |         |
| Very heavy                      | 278 (5.2)                      | 247 (5.0)    |         |

All P values were obtained by χ² test.
grade students (7 years of formal education); the mean age was 13.9 years (standard deviation: 0.7 year). About one half (47.0%) reported good/very good family financial status. Over 20% reported that either their father or mother had attended college or above; Majority of them (87.8%) lived with both parents. About one fifth reported lower academic performance (21.5%) and perceived heavy/very heavy academic pressure (23.9%) (Table 1). Of the participants, 4,951 (92.3%) were online social networking users. Their characteristics were also presented in Table 1. Online social networking users were more likely to be female, having an average/above average family financial status, and perceived an average level of academic pressure. Data obtained from the online social networking users were used for the LPA and ROC analyses.

Latent profile analysis (LPA)

In Fig. 1, the scree plot showed that the AIC, BIC and ssaBIC continuously decreased along increase in the number of latent classes. Two "elbow points" were found for the 3-class and 5-class solutions, suggesting that the goodness of fit was improved substantially when the number of latent classes increased from 1 to 2, from 2 to 3, and from 4 to 5, but not when another class was added to the 3-class and the 5-class models. The 3-class and 5-class models were preferred. The AIC, BIC and ssaBIC indices of both the 3-class (i.e., 99,162.03, 99,383.28 and 99,275.24) and 5-class (i.e., 89,226.53, 89,564.91 and 89,399.68) models were satisfactory. Fig. 2 showed the profiles of the 3-class model (Fig. 2a) and the 5-class model (Fig. 2b). While the 2–6 class models all showed entropies larger than the recommended value of 0.8, the 5-class model had the highest entropy of 0.966. The 3-class and 5-class models were potential candidates, as both of them met both the goodness of fit and entropy criteria. However, the size in one latent class of the 5-class model included less than 5% (i.e., 4.1%) of the total sample (see Table 2 and Fig. 2b), making it less preferred. Furthermore, the 3-class model but not the 5-class model was cross-validated in the split-sample validation analysis (see appendix Table S1). The high posterior probabilities of memberships of the three latent classes (0.944, 0.942, and 0.942, respectively) also indicate good discrimination. Thus, overall, the 3-class model was preferred and selected in our study. The logic of the decision for the number of latent classes is summarized in Fig. S1 (appendix).

Based on the 3-class model, participants were classified into the high-risk group, the average-risk group, and the low-risk group, which comprised 13.2%, 50.4%, and 36.4% of the participants, respectively (Table 2). In the subsequent ROC analysis, participants in the high-risk group were defined as "OSNA cases", while the rest (the average risk and low risk groups) were defined as "non-cases". The classification served as the reference standard.

ROC analysis

Using the binary outcomes ("case" and "non-case") obtained from LPA as the reference standard, the ROC plot of the sensitivity versus 1-specificity of various OSNA scale scores showed a very large area under the curve (AUC) of 0.989 (95% CI: 0.987, 0.991; P < 0.001). The diagnostic values

---

Fig. 1. Scree plot of AIC, BIC and ssaBIC versus number of latent class. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion; ssaBIC: sample size adjusted BIC
generated from the potential cut-off points of 19–28 are presented in Table 3. The maximum Youden index corresponded to the cut-off point of 23 (Youden index = 0.925), which yielded high sensitivity of 97.2%, specificity of 95.2%, positive predictive value of 75.5%, negative predictive value of 99.6%, and diagnostic accuracy of 95.5%, respectively (Table 3). The positive group (defined as OSNA scale score ≥23) included 17.0% of the participants.

Comparing levels of external factors between OSNA positive/negative groups (cut-off point of 23) and among latent classes derived from LPA

Participants in the positive group (OSNA score ≥23) were significantly more likely than those in the negative group (OSNA scale score <23) to exhibit: 1) higher intensity of online social networking use (i.e., longer duration of online social networking, more days per week using online social networking, and more time per day spent on online social networking); 2) inter-personal consequences related to online social networking use (i.e., more online social networking friends, and more frequent conflict with parents due to online social networking overuse); and 3) higher scores on the SFUI and EFUI subscales (P values <0.001; Table 4); 4) higher prevalence of Internet addiction (22.7 vs. 3.4%, P < 0.001; Table 4). The results showed significant correlations between OSNA (positive/negative status) and daily time spent on online social networking (Spearman r = 0.245, P < 0.001), conflict with parents due to online social networking overuse (Spearman r = 0.265, P < 0.001), and Internet addiction (Spearman r = 0.291, P < 0.001) (Table 4). The significant differences of external characteristics between the three latent classes as well as associations between external characteristics and the three latent classes were found (Table 4).

**DISCUSSION**

In this study, three latent classes were identified by LPA; 13.2% of the online social networking users were categorized into the high-risk group (“case” group) of OSNA and the rest (86.8%) into the “non-case” group accordingly. The ROC analysis selected the cut-off point of ≥23 as the optimal threshold to define probable OSNA, yielding high sensitivity of 97.2% and specificity of 95.2%. The positive and negative groups differed in duration, frequency and intensity related to online social networking use, and the prevalence of Internet addiction. Thus, acceptable external validity was suggested. The identified cut-off point would facilitate

---

**Table 2. Summary of latent profile analysis**

| No. of classes | Log-likelihood | Degree of freedom | AIC | BIC | ssaBIC | Entropy | BLRT | Probability of classes (%) (from low risk to high risk) |
|---------------|---------------|-------------------|-----|-----|--------|---------|------|---------------------------------------------------------|
| 1             | −56,629.709   | 16                | 113,291.42 | 113,395.535 | 113,344.692 | –      | –    | –                                                      |
| 2             | −51,683.614   | 25                | 103,417.23 | 103,579.911 | 103,500.47  | 0.801  | <0.001 | 61.0/39.0                                              |
| 3             | −49,547.014   | 34                | 99,162.03  | 99,383.277  | 99,275.237  | 0.870  | <0.001 | 36.4/50.4/13.2                                        |
| 4             | −48,856.359   | 43                | 97,798.72  | 98,078.535  | 97,941.896  | 0.875  | <0.001 | 36.6/43.6/8.8/11.0                                     |
| 5             | −44,561.266   | 52                | 89,226.53  | 89,564.914  | 89,399.677  | 0.966  | <0.001 | 36.3/11.6/38.0/10.0/4.1                                |
| 6             | −44,044.074   | 61                | 88,210.15  | 88,607.096  | 88,413.26   | 0.942  | <0.001 | 36.1/11.8/10.0/31.7/6.3/4.1                            |

---Not applicable. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion; ssaBIC: sample size adjusted BIC; BLRT: Bootstrapping Likelihood Ratio Test.
related research. For instance, further studies may use OSNA scale and its cut-off point to look at the relationships between OSNA and other specific types of Internet-related addictive behaviors (e.g., Internet gaming disorder, online gambling addiction) (Davis, 2001; Laconi, Tricard, & Chabrol, 2015; Tsitsika, Janikian et al., 2014).

Based on the selected cut-off point, the prevalence of OSNA among our sampled Chinese students was 17.0%. It was 4.5% among Hungarian adolescents, based on the 6-item Bergen Social Media Addiction Scale and the cut-off point of 19 (Banyai et al., 2017). In literature, the prevalence of OSNA among adolescents ranged from 0.6% to 47% (Brailovskaia & Margraf, 2017; Jafarkarimi, Sim, Saadatdoost, & Hee, 2016). A previous cross-region survey reported a higher risk of OSNA in Asian students compared with the U.S. students (Tang et al., 2018). The variations could be partially attributed to the differences in populations and measurement tools. Cautions should be taken when comparing OSNA prevalence across studies/regions.

The present study found that adolescents in the OSNA positive group (defined by the new cut-off point) reported more frequent conflict with their parents due to excessive online social networking use than those in the negative group. The finding corroborated previous studies that online social networking use was associated with adolescent–parents conflict (Gentzler, Oberhauser, Westerman, & Nadorff, 2011). In general, excessive involvement in online social networking may result in less time spent on other activities (e.g., communication with family and peers, academic study) (Mesch, 2003), inducing internalizing problems and poor academic performance. Such issues may harm adolescents' relationship with their parents (Tsitsika, Tzavela et al., 2014; Xin et al., 2018).

Adolescents are strongly affected by online social networking use (Mikami & Szved, 2014). Symptoms of OSNA are similar to those of substance addictions (Griffiths, 2013). The development of a cut-off point for the OSNA scale is essential. It is noteworthy that OSNA is currently recognized neither in the Diagnostic and Statistical Manual of Mental Disorders (5th edition), nor in the International Classification of Diseases (11th edition). It is also a limitation that the cut-off point was not determined by using the gold standard of clinical interviews. The classification result based on this study's cut-off point should thus be seen as “probable OSNA,” or an indication of very high risk of having OSNA, instead of high risk of having an addictive disorder. Since problematic online social networking use is prevalent and consequential, future studies should monitor its harms and develop effective interventions, as well as studying its relationships with other Internet-related disorders, such as Internet gaming disorder and Internet gambling disorder. The cut-off point identified in the present study contributes to such an end. The findings of this study are, however, suggestive. Future research can evaluate the performance of LPA cut-off points against the gold standards.

In general, under the strong demand for classification of populations into higher (positive) and lower risk (negative) groups for the purposes of epidemiological research (e.g., prevalence study and outcomes of randomized controlled trials) and interventions (e.g., secondary prevention interventions), derivation of cut-off points of screening tools is warranted. While gold standards are the best practice, they are sometimes unavailable. Under those circumstances, the LPA plus ROC approach can be used for selection of cut-off points for such assessment tools. Cut-off points based on LPA can facilitate epidemiological research and interventions by identifying positive groups, as positivity is defined as escalated likelihoods of having a health problem and its associated harms.

The study has several limitations. Data were self-reported and may be subjected to social desirability bias, although measures such as anonymity and absence of teachers have been taken in this study to reduce the bias. Generalizations should also be made with caution as the study was conducted in a relatively small number of schools in a single Chinese city. In addition, the sample included only 7th and 8th grade students, and the findings might be age dependent. It is useful to repeat similar exercises in other adolescent age groups and geographic regions. In addition, it should be emphasized that LPA is explorative in nature as the number of latent classes is determined by considering posterior fit
| Duration of online social networking use | Total \((n = 4,951)\) | The three latent classes | OSNA classification (cut-off: \(\geq 23\) for positive cases) | \(p^1\) | Spearman \(r\) |
|------------------------------------------|-----------------------|--------------------------|---------------------------------------------------|------|---------------|
| <1 year                                  | 1,018 (20.6)          | 485 (26.9)               | 430 (17.2)                                        | <0.001 | 0.093***      |
| 1–2 years                                | 995 (20.1)            | 332 (18.4)               | 538 (21.6)                                        | 125 (19.1) | 0.086*** |
| 2–3 years                                | 853 (17.3)            | 292 (16.2)               | 458 (18.4)                                        | 105 (16.1) | 0.076**      |
| 3–4 years                                | 803 (16.2)            | 263 (14.6)               | 434 (17.4)                                        | 106 (16.2) | 0.068**      |
| >4 years                                 | 1,280 (25.8)          | 433 (24.0)               | 633 (25.4)                                        | 214 (32.8) | 0.057**      |
| Number of days per week                  |                       |                          |                                                   |       |               |
| ≤1                                       | 1,141 (23.0)          | 642 (35.6)               | 424 (17.0)                                        | 75 (11.5) | <0.001       |
| 2–3 days                                 | 1,913 (38.6)          | 678 (37.6)               | 1,018 (40.8)                                      | 217 (33.2) | 0.252***    |
| 4–5 days                                 | 616 (12.4)            | 187 (10.4)               | 343 (13.8)                                        | 183 (26.2) | <0.001       |
| ≥6 days                                  | 1,281 (25.9)          | 298 (16.5)               | 708 (28.4)                                        | 275 (42.1) | <0.001       |
| Daily time spent on online social networking |               |                          |                                                   |       |               |
| <30 mins                                 | 840 (17.0)            | 514 (28.5)               | 278 (11.2)                                        | 48 (7.4) | <0.001       |
| 31–60 mins                               | 1,517 (30.6)          | 628 (34.8)               | 776 (31.1)                                        | 113 (17.3) | <0.001       |
| 1–2 hours                                | 1,289 (26.0)          | 397 (22.0)               | 727 (29.2)                                        | 165 (25.3) | <0.001       |
| 2–3 hours                                | 727 (14.7)            | 155 (8.6)                | 422 (16.9)                                        | 150 (23.0) | <0.001       |
| ≥3 hours                                 | 578 (11.7)            | 111 (6.1)                | 290 (11.6)                                        | 177 (27.1) | <0.001       |
| Number of online social networking friends |          |                          |                                                   |       |               |
| ≤50                                      | 1,869 (37.7)          | 807 (44.7)               | 861 (34.5)                                        | 201 (30.8) | <0.001       |
| 51–100                                   | 1,203 (24.3)          | 429 (23.8)               | 624 (25.0)                                        | 150 (23.0) | <0.001       |
| 101–200                                  | 1,079 (21.8)          | 340 (18.8)               | 601 (24.1)                                        | 138 (21.1) | <0.001       |
| 201–400                                  | 494 (10.0)            | 131 (7.3)                | 276 (11.1)                                        | 87 (13.3) | <0.001       |
| >400                                     | 306 (6.2)             | 98 (5.4)                 | 131 (5.3)                                         | 77 (11.8) | <0.001       |
| Conflict with parents due to online social networking overuse | | | | | |
| Never                                    | 1,438 (29.0)          | 827 (45.8)               | 522 (20.9)                                        | 89 (13.6) | <0.001       |
| Few                                      | 1,954 (39.5)          | 666 (36.9)               | 1,098 (44.0)                                      | 190 (29.1) | <0.001       |
| Occasional                               | 1,190 (24.0)          | 249 (13.8)               | 683 (27.4)                                        | 258 (39.5) | <0.001       |
| Always                                   | 369 (7.5)             | 63 (3.5)                 | 190 (7.6)                                         | 116 (17.8) | <0.001       |
| OSNAI scale                              |                      |                          |                                                   |       |               |
| SFUI                                     | 18.1 ± 8.5            | 15.9 ± 8.8               | 18.7 ± 7.8                                        | 21.6 ± 8.8 | <0.001       |
| EFUI                                     | 8.2 ± 3.2             | 7.4 ± 3.3                | 8.4 ± 2.9                                         | 9.4 ± 3.3 | <0.001       |
| Internet addiction                       |                       |                          |                                                   |       |               |
| No                                       | 4,621 (93.3)          | 1,770 (98.1)             | 2,356 (94.5)                                      | 495 (75.8) | <0.001       |
| Yes                                      | 330 (6.7)             | 35 (1.9)                 | 137 (5.5)                                         | 158 (24.2) | <0.001       |

OSNA: Online Social Networking Addiction; OSNAI: Online Social Networking Activity Intensity; SFUI: Social Function Use Intensity; EFUI: Entertainment Function Use Intensity.

Spearman \(r\): Spearman correlation coefficients.

\(^1\): \(p\) values were obtained by \(\chi^2\) test for categorical variables, independent-sample \(t\)-test for two-group continuous variables, and one-way analysis of variance for three-group continuous variables.

***: \(p < 0.001\) for Spearman correlation coefficients.
statistics, interpretability, and utility. There might be misclassifications, and the identified cut-off point should be validated by using gold standards of clinical diagnosis in future research.

All in all, the findings contribute to the future development of cut-off points for Internet-related assessment tools in specific and other tools in general. Researchers may conduct longitudinal studies in the future to understand efficacy of OSNA and the identified cut-off point in predicting behavioral and health outcomes.

**Funding sources:** The study was supported by the National Natural Science Foundation of China (No.: 81373021), and was also supported by the Jockey Club School of Public Health and Primary Care Research Postgraduate Students’ Research Grants and CUHK research Postgraduate Student Grants for Overseas Academic Activities in the Chinese University of Hong Kong. The funding sources had no role in the design and conduct of the study collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.

**Authors’ contribution:** JB Li, PKH Mo, and JTF Lau conceived and designed the study. JB Li, JC Mai, and YX Chen acquired the data. JB Li, LF Feng, and Y Deng did the statistical analyses. JB Li, AMS Wu, LF Feng, Y Deng, JH Li, YX Chen, JC Mai, PKH Mo, and JTF Lau drafted and revised the manuscript. All authors contributed to the interpretation of the results and critical revision of the manuscript for important intellectual content and approved the final version of the manuscript.

**Conflict of interest:** The authors declare no conflict of interest.

**Acknowledgments:** The authors would like to thank all participants, their families, and schools, as well as all field workers, for their contribution to this study. We would also like to express our gratitude to Dr. Xue-fen Su for her assistance in data collection.

**REFERENCES**

Aboujaoude, E. (2010). Problematic internet use: An overview. *World Psychiatry*, 9(2), 85–90. [https://doi.org/10.1002/j.2051-5545.2010.tb00278.x](https://doi.org/10.1002/j.2051-5545.2010.tb00278.x).

Akobeng, A. K. (2007). Understanding diagnostic tests 3: Receiver operating characteristic curves. *Acta Paediatrica*, 96(5), 644–647. [https://doi.org/10.1111/j.1651-2227.2006.00178.x](https://doi.org/10.1111/j.1651-2227.2006.00178.x).

Andreassen, C. S. (2015). Online social network site addiction: A comprehensive review. *Current Addiction Reports*, 2(2), 175–184. [https://doi.org/10.1007/s40429-015-0056-9](https://doi.org/10.1007/s40429-015-0056-9).

Banyai, F., Zsila, A., Kiraly, O., Maraz, A., Elekes, Z., Griffiths, M. D., et al. (2017). Problematic social media use: Results from a large-scale nationally representative adolescent sample. *PLoS One*, 12(1), e0169839. [https://doi.org/10.1371/journal.pone.0169839](https://doi.org/10.1371/journal.pone.0169839).

Brailovskaia, J., & Margraf, J. (2017). Facebook Addiction Disorder (FAD) among German students-A longitudinal approach. *PLoS One*, 12(12), e0189719. [https://doi.org/10.1371/journal.pone.0189719](https://doi.org/10.1371/journal.pone.0189719).

Brar, S. K., Beattie, T. S. H., Abas, M., Vansa, D., Phanga, T., Maseko, B., et al. (2020). The relationship between intimate partner violence and probable depression among adolescent girls and young women in Lilongwe, Malawi. *Glob Public Health*, 1–12. [https://doi.org/10.1080/17441692.2020.1718732](https://doi.org/10.1080/17441692.2020.1718732).

Bull, S. S., Levine, D. K., Black, S. R., Schmiege, S. J., & Santelli, J. (2012). Social media-delivered sexual health intervention: A cluster randomized controlled trial. *American Journal of Preventive Medicine*, 43(5), 467–474. [https://doi.org/10.1016/j.amepre.2012.07.022](https://doi.org/10.1016/j.amepre.2012.07.022).

Byun, S., Ruffini, C., Mills, J. E., Douglas, A. C., Niang, M., Stepchenkova, S., et al. (2009). Internet addiction: Metasynthesis of 1996–2006 quantitative research. *CyberPsychology and Behavior*, 12(2), 203–207. [https://doi.org/10.1089/cpb.2008.0102](https://doi.org/10.1089/cpb.2008.0102).

Davis, R. A. (2001). A cognitive-behavioral model of pathological Internet use. *Computers in Human Behavior*, 17(2), 187–195. [https://doi.org/10.1016/S0747-5632(00)00041-8](https://doi.org/10.1016/S0747-5632(00)00041-8).

De Cock, R., Vangeel, J., Klein, A., Minotte, P., Rosas, O., & Gert-Jan, M. (2014). Compulsive use of social networking sites in Belgium: Prevalence, profile, and the role of attitude toward work and school. *Cyberpsychology, Behavior, and Social Networking*, 17(3), 166–171. [https://doi.org/10.1089/cyber.2013.0029](https://doi.org/10.1089/cyber.2013.0029).

Echeburua, E., & De Corral, P. (2010). Addiction to new technologies and to online social networking in young people: A new challenge. *Addiciones*, 22(2), 91–95.

Fonseca-Pedrero, E., Ortuño-Sierra, J., de Albeniz, A. P., Muniz, J., & Cohen, A. S. (2017). A latent profile analysis of schizotypal dimensions: Associations with psychopathology and personality. *Psychiatry Research*, 253, 110–115. [https://doi.org/10.1016/j.psychres.2017.02.038](https://doi.org/10.1016/j.psychres.2017.02.038).

Garrett, E. S., Eaton, W. W., & Zeger, S. (2002). Methods for evaluating the performance of diagnostic tests in the absence of a gold standard: A latent class model approach. *Statistics in Medicine*, 21(9), 1289–1307. [https://doi.org/10.1002/sim.1105](https://doi.org/10.1002/sim.1105).

Gentzler, A. L., Oberhauser, A. M., Westerman, D., & Nadorff, D. K. (2011). College students’ use of electronic communication with parents: Links to loneliness, attachment, and relationship quality. *Cyberpsychology, Behavior, and Social Networking*, 14(1–2), 71–74. [https://doi.org/10.1089/cyber.2009.0409](https://doi.org/10.1089/cyber.2009.0409).

Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance Use*, 10(4), 191–197.

Griffiths, M. D. (2013). Social networking addiction: Emerging themes and issues. *Journal of Addiction Research & Therapy*, 4(5), e118. [https://doi.org/10.4172/2155-6105.1000e118](https://doi.org/10.4172/2155-6105.1000e118).

Griths, M. D., Kuss, D. J., & Demetrovics, Z. (2014). Social networking addiction: An overview of preliminary findings. In K. P. Rosenberg & L. C. Feder (Eds.), *Behavioral addictions: Criteria, Evidence and treatment* (pp. 119–141). London: Elsevier.
Hornes, J. M., Kearns, B., & Timko, C. A. (2014). Craving Facebook? Behavioral addiction to online social networking and its association with emotion regulation deficits. *Addiction, 109*(12), 2079–2088.

Jafarkarimi, H., Sim, A. T. H., Saadatdoost, R., & Hee, J. M. (2016). Facebook addiction among Malaysian students. *International Journal of Information and Education Technology, 6*(6), 465–469. doi:10.7763/IJIET.2016.V6.733.

Kiraly, O., Slezcka, P., Pontes, H. M., Urban, R., Griffiths, M. D., & Demetrovics, Z. (2017). Validation of the ten-item internet gaming disorder test (IGDT-10) and evaluation of the nine DSM-5 internet gaming disorder criteria. *Addictive Behaviors, 64*, 253–260. https://doi.org/10.1016/j.addbeh.2015.11.005.

Ko, C. H., Yen, J. Y., Chen, S. H., Yang, M. J., Lin, H. C., & Yen, C. F. (2009). Proposed diagnostic criteria and the screening and diagnosing tool of Internet addiction in college students. *Comprehensive Psychiatry, 50*(4), 378–384. https://doi.org/10.1016/j.comppsych.2007.05.019.

Koc, M., & Gulyagi, S. (2015). Facebook addiction among Turkish college students: The role of psychological health, demographic, and usage characteristics. *Cyberpsychology, Behavior, and Social Networking, 16*(4), 279–284. https://doi.org/10.1089/cyper.2012.0249.

Kormas, G., Critselis, E., Janikian, M., Kafetzis, D., & Tsitsika, A. (2011). Risk factors and psychosocial characteristics of potential problematic and problematic internet use among adolescents: A cross-sectional study. *BMC Public Health, 11*(1), 595–602. https://doi.org/10.1186/1471-2458-11-595.

Lacović, S., Tricard, N., & Chabrol, H. (2015). Differences between specific and generalized problematic Internet use according to gender, age, time spent online and psychopathological symptoms. *Computers in Human Behavior, 48*, 236–244. https://doi.org/10.1016/j.chb.2015.02.006.

Li, J. B., Lau, J. T., Mo, P. K. S., Su, X., Wu, A. M., Tang, J., et al. (2016). Validation of the social networking activity intensity scale among junior middle school students in China. *PLoS One, 11*(10), e0165695. https://doi.org/10.1371/journal.pone.0165695.

Li, J. B., Mo, P. K. S., Lau, J. T. F., Su, X. F., Zhang, X., Wu, A. M. S., et al. (2018). Online social networking addiction and depression: The results from a large-scale prospective cohort study in Chinese adolescents. *Journal of Behavioral Addictions, 7*(3), 686–696. https://doi.org/10.1556/2206.2006.7.2018.69.

Li, Y., Zhang, X., Lu, F., Zhang, Q., & Wang, Y. (2014). Internet addiction among elementary and middle school students in China: A nationally representative sample study. *Cyberpsychology, Behavior, and Social Networking, 17*(2), 111–116. https://doi.org/10.1089/cyper.2012.0482.

Livingstone, S., Haddon, L., Görzig, A., & Ólafsson, K. (2011). *EU kids online: Final report*. London, UK: EU Kids Online, London School of Economics & Political Science.

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. In T. D. Little (Ed.), *The Oxford handbook of quantitative methods: Vol. 2. Statistical analysis* (pp. 551–611). New York: Oxford University Press.

Mesch, G. S. (2003). The family and the internet: The Israeli case*. *Social Science Quarterly, 84*(4), 1038–1050.

Mikami, A. Y., & Szwebo, D. E. (2014). Social networking in online and offline contexts. In R. J. R. Levesque (Ed.), *Encyclopedia of adolescence* (pp. 2801–2808). New York: Springer.

Nagin, D. (2005). *Group-based modeling of development*. Cambridge, MA: Harvard University Press.

Nyhus-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science, 4*(4), 440–461. https://doi.org/10.1037/tpi0000176.

Pantic, I. (2014). Online social networking and mental health. *Cyberpsychology, Behavior, and Social Networking, 17*(10), 652–657. https://doi.org/10.1089/cyber.2014.0070.

Ryan, T., Chester, A., Reece, J., & Xenos, S. (2014). The uses and abuses of Facebook: A review of Facebook addiction. *Journal of Behavioral Addictions, 3*(3), 133–148. https://doi.org/10.1556/JBA.3.2014.016.

Shi, J. Q., & Niu, Q. Q. (2010). SNSs usage among Chinese internet users: An empirical study. In B. K. Wiederhold, G. Riva, & S. I. Kim (Eds.), *Annual review of cybertherapy and telemedicine 2010: Advanced technologies in behavioral, social and neurosciences* (Vol. 154, pp. 150–154). Washington, DC: IOS Press.

Shirmohammadi, N., Soltanian, A. R., & Borzouei, S. (2018). Public awareness of early and late complications of type 2 diabetes – Application of latent profile Analysis in determining questionnaire cut-off points. *Osong Public Health Res Perspect, 9*(5), 261–268. https://doi.org/10.14211/j.phrp.2018.9.5.08.

van Smeden, M., Naaktgeboren, C. A., Reitsma, J. B., Moons, K. G., & de Groot, J. A. (2014). Latent class models in diagnostic studies when there is no reference standard–a systematic review. *American Journal of Epidemiology, 179*(4), 423–431. https://doi.org/10.1093/aje/kwt286.

Tang, C. S. K., Wu, A. M. S., Yan, E. C. W., Ko, J. H. C., Kwon, J. H., Yogo, M., et al. (2018). Relative risks of Internet-related addictions and mood disturbances among college students: A 7-country/region comparison. *Public Health, 165*, 16–25. https://doi.org/10.1016/j.puhe.2018.09.010.

Tsitsika, A., Janikian, M., Schoenmakers, T. M., Tzavela, E. C., Olafsson, K., Wójcik, S., et al. (2014). Internet addictive behavior in adolescence: A cross-sectional study in seven European countries. *Cyberpsychology, Behavior, and Social Networking, 17*(8), 528–535. https://doi.org/10.1089/cyper.2013.0382.

Tsitsika, A. K., Tzavela, E. C., Janikian, M., Olafsson, K., Iordanche, A., Schoenmakers, T. M., et al. (2014). Online social networking in adolescence: Patterns of use in six European countries and links with psychosocial functioning. *Journal of Adolescent Health, 55*(1), 141–147. https://doi.org/10.1016/j.jadohealth.2013.11.010.

Wendt, L. P., Wright, A. G. C., Pilkonis, P. A., Nolte, T., Fonagy, P., Montague, P. R., et al. (2019). The latent structure of interpersonal problems: Validity of dimensional, categorical, and hybrid models. *Journal of Abnormal Psychology, 128*(8), 823–839. https://doi.org/10.1037/abn0000460.

Xin, M., Xing, J., Pengfei, W., et al. (2018). Online activities, prevalence of Internet addiction and risk factors related to family and school among adolescents in China. *Addictive Behaviors Reports, 7*, 14–18. https://doi.org/10.1016/j.jabrep.2017.10.003.

Young, K. S. (1998). Internet addiction: The emergence of a new clinical disorder. *CyberPsychology and Behavior, 1*(3), 237–244. https://doi.org/10.1089/cyber.1998.1.237.
Zhang, Z., Zhang, G., Goyal, H., Mo, L., & Hong, Y. (2018). Identification of subclasses of sepsis that showed different clinical outcomes and responses to amount of fluid resuscitation: A latent profile analysis. *Critical Care, 22*(1), 347. https://doi.org/10.1186/s13054-018-2279-3.

**SUPPLEMENTARY MATERIAL**

The online version of this article offers supplementary material (https://doi.org/10.1556/2006.2020.00047).

---

**Open Access statement.** This is an open-access article distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (https://creativecommons.org/licenses/by-nc/4.0/), which permits unrestricted use, distribution, and reproduction in any medium for non-commercial purposes, provided the original author and source are credited, a link to the CC License is provided, and changes – if any – are indicated.