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FULL-LENGTH REPORT

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

JI-BIN LI[1,2,3*], ANISE M.S. WU[4], LI-FEN FENG[5], YANG DENG[6], JING-HUA LI[6], YU-XIA CHEN[7], JIN-CHEN MAI[7], PHOENIX K.H. MO[3**] and JOSEPH T.F. LAU[3***]

[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

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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

*Corresponding author.
E-mail: lijib@sysucc.org.cn

**Corresponding author.
E-mail: phoenix.mo@cuhk.edu.hk

***Corresponding author.
E-mail: jlau@cuhk.edu.hk

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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, & Ólafsson, 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 interactions among 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; Kormas, 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 with 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 [χ^2 = 448.7 (P < 0.001), CFI = 0.97, and RMSEA = 0.074 (90% CI: 0.068, 0.080)]. The standardized path estimates ranged from 0.60 to 0.78], and the Cronbach's α 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 α 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 α 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 (ssaBIC) 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 χ^2 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	
	Total (n = 5,365)	Yes (n = 4,951)	*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 χ^2 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 was 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

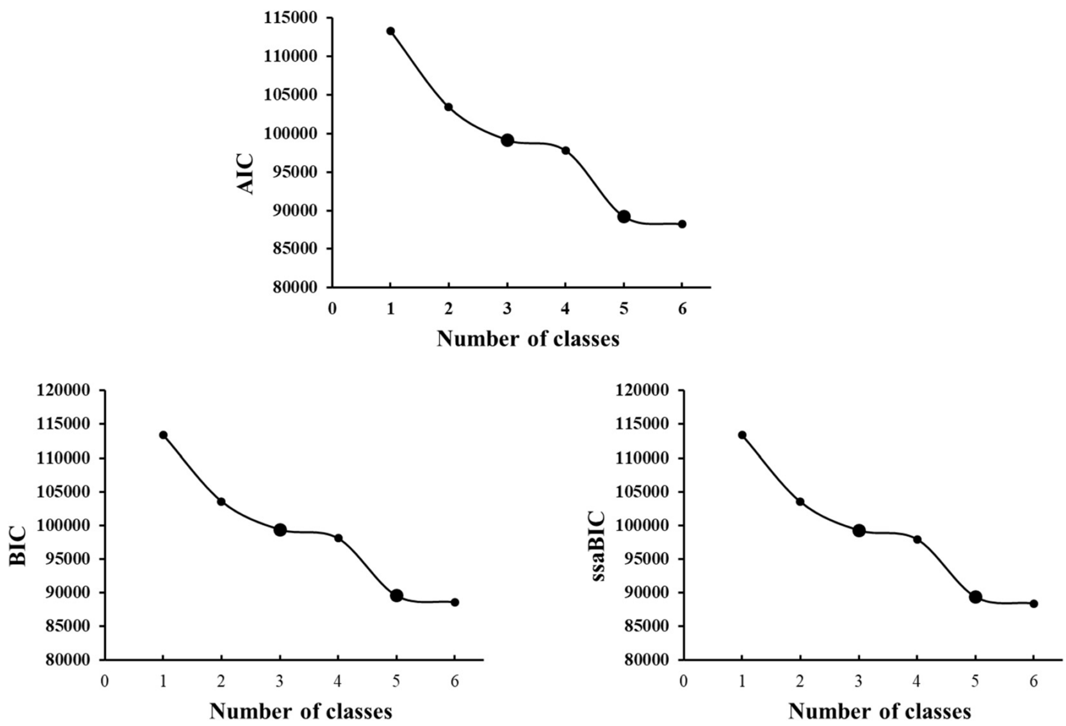

Fig. 1. Scree plot of AIC, BIC and ssaBIC versus number of latent class. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion; ssaBIC: sample size adjusted BIC

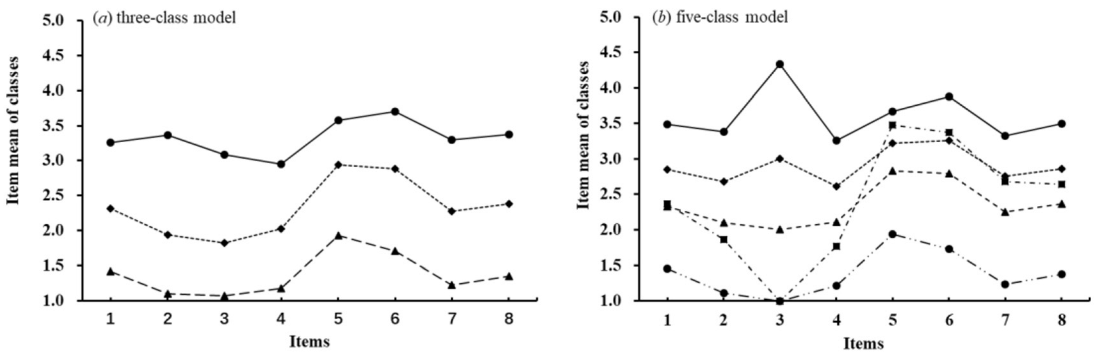

Fig. 2. Distributions of items means in three (*a*) and five (*b*) latent class models in the whole sample. Item 1: I have difficulties for focusing on my academic work due to my online social networking use; Item 2: The first thing on my mind when I get up is to log into online social networking; Item 3: I lose sleep over spending more time on online social networking; Item 4: My online social networking use interferes with doing social activities; Item 5: I log into online social networking to make myself feel better when I am down; Item 6: My family or friends think that I spend too much time on online social networking; Item 7: I feel anxious if I cannot access to online social networking; Item 8: I have attempted to spend less time on online social networking but have not succeeded

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 use, 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.

Table 3. ROC analysis of the online social networking addiction scale using the high-risk class derived from latent profile model as gold standard

Cut-off point	True positive	False negative	True negative	False positive	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	Accuracy (%)	Youden index
19	653	0	3,125	1,173	100.0	72.7	35.8	100.0	76.3	72.7
20	653	0	3,449	849	100.0	80.2	43.5	100.0	82.9	80.2
21	652	1	3,714	584	99.8	86.4	52.8	100.0	88.2	86.3
22	649	4	3,937	361	99.4	91.6	64.3	99.9	92.6	91.0
23	635	18	4,092	206	97.2	95.2	75.5	99.6	95.5	92.5
24	590	63	4,193	105	90.4	97.6	84.9	98.5	96.6	87.9
25	409	244	4,248	50	62.6	98.8	89.1	94.6	94.1	61.5
26	331	322	4,283	15	50.7	99.7	95.7	93.0	93.2	50.3
27	257	396	4,296	2	39.4	100.0	99.2	91.6	92.0	39.3
28	196	457	4,297	1	30.0	100.0	99.5	90.4	90.7	30.0

PPV: Positive predictive value; NPV: Negative predictive value.

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 & Szwedo, 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 circumstance, 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

Table 4. Comparison of external factors between three latent classes, and between OSNA positive and negative groups

		The three latent classes					OSNA classification (cut-off: ≥23 for positive cases)			
	Total (n = 4,951)	Low risk (n = 1,805)	Average-risk (n = 2,493)	High-risk (n = 653)	$P^{\dagger}$	Spearman r	Negative (n = 4,110)	Positive (n = 841)	$P^{\dagger}$	Spearman r
Duration of online social networking use										
<1 year	1,018 (20.6)	485 (26.9)	430 (17.2)	103 (15.8)	<0.001	0.093***	893 (21.7)	125 (14.9)	<0.001	0.086***
1–2 years	995 (20.1)	332 (18.4)	538 (21.6)	125 (19.1)			838 (20.4)	157 (18.7)		
2–3 years	855 (17.3)	292 (16.2)	458 (18.4)	105 (16.1)			717 (17.4)	138 (16.4)		
3–4 years	803 (16.2)	263 (14.6)	434 (17.4)	106 (16.2)			661 (16.1)	142 (16.9)		
>4 years	1,280 (25.8)	433 (24.0)	633 (25.4)	214 (32.8)			1,001 (24.4)	279 (33.2)		
Number of days per week										
≤1	1,141 (23.0)	642 (35.6)	424 (17.0)	75 (11.5)	<0.001	0.252***	1,057 (25.7)	84 (10.0)	<0.001	0.183***
2–3 days	1,913 (38.6)	678 (37.6)	1,018 (40.8)	217 (33.2)			1,614 (39.3)	299 (35.6)		
4–5 days	616 (12.4)	187 (10.4)	343 (13.8)	86 (13.2)			506 (12.3)	110 (13.1)		
≥6 days	1,281 (25.9)	298 (16.5)	708 (28.4)	275 (42.1)			933 (22.7)	348 (41.4)		
Daily time spent on online social networking										
<30 mins	840 (17.0)	514 (28.5)	278 (11.2)	48 (7.4)	<0.001	0.311***	782 (19.0)	58 (6.9)	<0.001	0.245***
31–60 mins	1,517 (30.6)	628 (34.8)	776 (31.1)	113 (17.3)			1,367 (33.3)	150 (17.8)		
1–2 hours	1,289 (26.0)	397 (22.0)	727 (29.2)	165 (25.3)			1,063 (25.9)	226 (26.9)		
2–3 hours	727 (14.7)	155 (8.6)	422 (16.9)	150 (23.0)			535 (13.0)	192 (22.8)		
>3 hours	578 (11.7)	111 (6.1)	290 (11.6)	177 (27.1)			363 (8.8)	215 (25.6)		
Number of online social networking friends										
≤50	1,869 (37.7)	807 (44.7)	861 (34.5)	201 (30.8)	<0.001	0.127***	1,618 (39.4)	251 (29.8)	<0.001	0.104***
51–100	1,203 (24.3)	429 (23.8)	624 (25.0)	150 (23.0)			1,011 (24.6)	192 (22.8)		
101–200	1,079 (21.8)	340 (18.8)	601 (24.1)	138 (21.1)			887 (21.6)	192 (22.8)		
201–400	494 (10.0)	131 (7.3)	276 (11.1)	87 (13.3)			382 (9.3)	112 (13.3)		
>400	306 (6.2)	98 (5.4)	131 (5.3)	77 (11.8)			212 (5.2)	94 (11.2)		
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	0.329***	1,333 (32.4)	105 (12.5)	<0.001	0.265***
Few	1,954 (39.5)	666 (36.9)	1,098 (44.0)	190 (29.1)			1,708 (41.6)	246 (29.3)		
Occasional	1,190 (24.0)	249 (13.8)	683 (27.4)	258 (39.5)			863 (21.0)	327 (38.9)		
Always	369 (7.5)	63 (3.5)	190 (7.6)	116 (17.8)			206 (5.0)	163 (19.4)		
OSNAI scale										
SFUI	18.1 ± 8.5	15.9 ± 8.8	18.7 ± 7.8	21.6 ± 8.8	<0.001	0.218***	17.3 ± 8.2	22.0 ± 8.8	<0.001	0.199***
EFUI	8.2 ± 3.2	7.4 ± 3.3	8.4 ± 2.9	9.4 ± 3.3	<0.001	0.194***	7.9 ± 3.1	9.5 ± 3.3	<0.001	0.178***
Internet addiction										
No	4,621 (93.3)	1,770 (98.1)	2,356 (94.5)	495 (75.8)	<0.001	0.227***	3,937 (96.6)	650 (77.3)	<0.001	0.291***
Yes	330 (6.7)	35 (1.9)	137 (5.5)	158 (24.2)			139 (3.4)	191 (22.7)		

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.

†: P values were obtained by χ^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.

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SUPPLEMENTARY MATERIAL

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