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FULL-LENGTH REPORT

Classification of nomophobia among Chinese college students: Evidence from latent profile and ROC analysis

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ABSTRACT

Background and aims: Nomophobia (NMP) is a contemporary digital ailment referring to the improper utilization of smartphones which can have significant impacts on the physical and mental health of college students. However, as a result of unclear cutoff points, the proportion of people with NMP may be exaggerated. This study therefore aimed to determine the critical value of NMP and assess the extent to which Chinese college students are impacted by NMP using the Nomophobia Questionnaire (NMP-Q). *Methods:* Latent profile analysis (LPA) and the receiver operating characteristic curve (ROC) were combined to determine the critical value based on NMP-Q scores using a large sample of 3,998 college students (M_{age} = 20.58; SD = 1.87). *Results:* Based on latent profile (i.e., *at-risk NMP* group), ROC revealed an optimal cut-off point of 73 (Sensitivity = 0.965, Specificity = 0.970, Accuracy = 0.968, AUC = 99.60%, Youden's index = 0.935), and the percentage of NMP students being 28.04%, with 1,121 participants identified as positive cases (probable cases). Positive cases were found to exhibit more severe depression and anxiety symptoms, with a higher proportion of females were observed in the positive group (N = 829; 73.95%). *Conclusions:* These findings provide evidence that the proportion of NMP individuals may have been overestimated in the past. Furthermore, this study helps to validate the NMP-Q as a valid tool to identify NMP in college-aged individuals.

KEYWORDS

nomophobia, LPA, ROC, cut-off scores, Chinese college students

INTRODUCTION

Throughout the past two decades, the continuous evolution of smartphones has had an ongoing dramatic impact on human lifestyles, becoming an indispensable part of our modern life (King, Valença, & Nardi, 2010; Kubi, Saleem, & Popov, 2011; Parasuraman, Sam, Yee, Chuon, & Ren, 2017). Due to the conveniences provided by smartphones, people have become overly dependent on them (van Deursen, Bolle, Hegner, & Kommers, 2015), which has led to more problematic phone use behaviors (PPU; Horwood & Anglim, 2018). Furthermore, excessive smartphone use has been commonly associated with psychological and behavioral adjustment problems (e.g., depression, anxiety, perceived stress, poor sleeping quality; Sohn, Rees, Wildridge, Kalk, & Carter, 2019), and have been shown to even cause subsequent mental health problem such as nomophobia (Bhattacharya, Bashar, Srivastava, & Singh, 2019).

Nomophobia (NMP) refers to the anxiety and discomfort caused by one's inability to use their smartphone, or by one not having a smartphone nearby, and has drawn growing

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attention (King et al., 2010, 2013). Currently, NMP remains unclassified within established diagnostic categories as a mental disorder. It is worth noting that NMP has been proposed for inclusion in the Diagnostic and Statistical Manual of Mental Disorders (DSM-V) and has been regarded as a specific anxiety disorder by certain scholars (Bragazzi & Del Puente, 2014; Yildirim & Correia, 2015). Individuals with NMP tend to exhibit a series of symptoms of mental problems such as anxiety, depression, and agitation, and even developing respiratory alterations, trembling, and disorientation amongst other physical symptoms (Bhattacharya et al., 2019; Nurwahyuni, 2018). It has also been suggested that NMP may impair one's personal social adjustment, or disrupting peer and family relationships (Morahan-Martin & Schumacher, 2000) and academic achievements (Nurwahyuni, 2018). With such a broad range of serious impacts, it is essential to identify individuals suffering from NMP in order to provide them with interventions, and to clarify the relationship between NMP and other functional disorders (e.g., social panic disorder; King et al., 2010; King et al., 2014).

Measurement, proportion, and cut-off point of nomophobia

Although NMP has been suggested to be treated as a special diagnosis category of anxiety disorder, it can be difficult to distinguish whether an individual does in fact have NMP or not (Bragazzi & Del Puente, 2014; Yildirim & Correia, 2015). Some instruments have been developed to assist in its measurement, including the Nomophobia Questionnaire (NMP-Q; Yildirim & Correia, 2015), the Questionnaire to Assess Nomophobia (QANP; Ferri-García, Olivencia-Carrión, Rueda, Jiménez-Torres, & López-Torrecillas, 2019), and the Fırat Nomophobia Scale (Kanbay, Akçam, Özbay, Özbay, & Fırat, 2022). Of these, the NMP-Q is currently the most popular scale and used widely and has been translated into more than 10 different languages including but not limited to European Portuguese (Galhardo, Loureiro, Massano-Cardoso, & Cunha, 2023), Spanish (González-Cabrera, León-Mejía, Pérez-Sancho, & Calvete, 2017), Turkish (Yildirim, Sumuer, Adnan, & Yildirim, 2016), and Chinese (Ma & Liu, 2021). Using a qualitative interview approach, Yildirim and Correia (2015) proposed four dimensions of NMP: fear of not being able to communicate (FNC), fear of losing connectedness (FLC), fear of not being able to access information (FNI), and fear giving up convenience (FGC). Based on this theoretical assumption, the four-factor model was used to develop the NMP-Q to evaluate individuals' level of NMP (Yildirim & Correia, 2015). It consists of 20 items measuring the four dimensions: six items assess FNC (e.g., "If I did not have my smartphone with me, I would be worried because my family and/or friends could not reach me."); five items assess FLC (e.g., "If I did not have a data signal or could not connect to Wi-Fi, then I would constantly check to see if I had a signal or could find a Wi-Fi network."); four items assess FNI (e.g., "If I did not have my smartphone with me, I would feel uncomfortable without constant access to information through my smartphone."); and five items assess FGC (e.g., "If I did not have my smartphone with me, would feel anxious because I could not check my email messages."). Higher total scores indicate a more severe level of NMP. This scale has demonstrated excellent psychometric properties in previous studies (Galhardo et al., 2023; Ma & Liu, 2021; Yildirim & Correia, 2015).

Despite the scale has come to be widely used, there appears to be a wide range in the proportion of NMP individuals as found in previous studies (León-Mejía, Gutiérrez-Ortega, Serrano-Pintado, & González-Cabrera, 2021). For instance, Yildirim et al. (2016), as well as Ma and Liu (2021) both employed convenience sampling methods to investigate the proportion of NMP individuals. Yildirim et al. (2016) identified a NMP prevalence of 42.6% among 537 college students in Turkey, whereas Ma and Liu (2021) discovered a notably high percentage of 82.9% participants suffering from NMP in Chinese populations. Moreover, evidence from a systematic review suggested that females and young adults were found to be more vulnerable to NMP compared to other age groups, with NMP rates ranging from 6% to 73% (León-Mejía et al., 2021). Particularly, a recent meta-analysis revealed that the overall incidence of NMP among university students has reached potentially alarming levels, with Tuco, Castro-Diaz, Soriano-Moreno, and Benites-Zapata (2023) reporting a proportion of nearly 100%. Among these students, 56% reported experiencing moderate symptoms, while 17% reported severe symptoms (Tuco et al., 2023). This wide range of diversity in the proportion of NMP individuals may be partly attributed to changes in society and lifestyle leading to an increasing number of individuals suffering from NMP (van Deursen et al., 2015), as well as to diversity in populations (e.g., Western compared to non-Western countries; Li et al., 2020). However, these extreme values are more likely due to inappropriate scoring criteria (Li et al., 2020), which can result in the over- or underestimation of NMP levels in the general population.

Many studies have adopted a range of cutoff points to evaluate NMP on the NMP-Q scale (e.g., Galhardo et al., 2023; Ma & Liu, 2021). For example, some studies classified participants into three levels of NMP: none to mild (20–59 scores)/moderate (60–99 scores)/severe (100–140 scores; Deryakulu & Ursavaş, 2019), or occasional (15th percentile)/at-risk (80th percentile)/problematic users (95th percentile; Galhardo et al., 2023). In certain studies, participants have been categorized into four levels: absence (20 scores)/mild (21–59 scores)/moderate (60–99 scores)/severe (100–120 scores; Sharma, Mathur, & Jeenger, 2019; Yildirim et al., 2016). Other studies have classified NMP into five levels, according to standardized NMP-Q scores (i.e., Z-score): absence (<−1)/low (−1 to 0)/mild (0–1)/severe (1–2)/extremely severe (>2; Ma & Liu, 2021). However, variations in thresholds can lead to fluctuations in the detection rates of NMP across different studies, posing a challenge in effectively comparing them due to the absence of convincing scoring criteria.

Clinical results have traditionally been considered the gold standard for the evaluation of a screening tool's efficacy and determining the optimal critical values (Li et al., 2020).

However, in the absence of clinical results, a combined approach of latent profile analysis (LPA) and receiver operating characteristic (ROC) analysis can be used as an alternative solution to address issues of critical values (Bányai et al., 2017; Király et al., 2017; Li et al., 2020). LPA is a person-centered statistical method that enables the generation of unobserved, homogeneous subgroups with their own probability distributions (Marsh, Lüdtke, Trautwein, & Morin, 2009). It has been shown to result in lower rates of misclassification and missing data (Magidson & Vermunt, 2002). To establish the critical value, the latent profile representing the most severe level of the disorder is considered to be the "case" group, and the remaining participants are then categorized as the "non-case" group for sensitivity analysis of the ROC (Li et al., 2020). After the ROC analysis, individuals who score at or above the critical value can then be identified as "probable case" (i.e., probable positive case), indicating a higher risk of them experiencing the disorder in question, and its associated harms – in the case of this study, NMP.

The current study

The purpose of this study was to establish cut-off point for identifying functional impairment in Chinese young adults in particular. To achieve this goal, a combination method of LPA and ROC analysis was adopted to derive a critical value for the Chinese version of the NMP-Q.

First, LPA was conducted to identify the homogenous subgroups of NMP and to further determine the reference groups (i.e., the "case" group and the "non-case" group). Second, ROC analysis was performed using the reference groups established through LPA to determine the optimal cut-off point. Individuals whose scores were at or above the selected cut-off point (i.e., in the probable positive group) were used to determine the proportion of NMP. Finally, to validate the critical value and gather evidence for the application of the NMP-Q in this study, chi-square values and odds ratios (ORs) were calculated to examine the relationships among reference groups, screening groups (i.e., positive group and negative group), and external variables (e.g., gender, anxiety, and depression).

METHODS

Participants

This study focused on college students as its target population. The initial sample for this study consisted of 4,046 participants from nine provinces and municipalities in China, including Beijing, Tianjin, and Chongqing, covering both northern and southern regions of the nation. The data collection process involved a combination of offline (Sample 1: 1,745 respondents) and online (Sample 2: 2,301 respondents) methods. Little's MCAR test confirmed that the missingness of data was completely random (MCAR, $\chi^2 = 454.55$, $p = 0.52$), and returned data with consistently similar responses or missing values exceeding 20% were deemed to be excluded, resulting in the removal of the data of 48 participants. The final sample ($N = 3{,}998$) was composed of 1,363 males (34.09%), 2,624 females (65.63%), and 11 participants (0.28%) who did not report their gender. The average age of participants was 20.58 ($SD = 1.87$). Among the total sample, freshmen constituted the largest group ($N = 1{,}658$, 41.47%), sophomores accounted for 29.79% ($N = 1{,}191$), juniors comprised 23.46% ($N = 938$), seniors made up 3.88% ($N = 155$), and a small portion of 1.40% ($N = 56$) failed to provide their grade information.

Procedure

The data collection process took place either in a formal classroom setting during a regular school day or through online platform of "wenjuanxing". All participants were briefed on in paper or electronic form the purpose of the study, the confidentiality, anonymity, voluntary participation, the option to withdraw freely, as well as absence of compensation for their involvement. Only those who have provided written consent (for offline participants) or have checked "I have read the above information and agree to participate in this study" (for online participants) were eligible to participate in the survey. It typically took them 10–15 min to complete the entire questionnaire. All research assistants assisting in the data collection were professionally trained.

Measures

The Nomophobia Questionnaire (NMP-Q). The NMP-Q was designed by Yildirim and Correia (2015) to assess the anxiety or panic state experienced by individuals when they are unable to use or are separated from their smartphone. The scale consists of 20 items measuring four dimensions: FNC, FLC, FNI and FGC. Each item is rated on a seven-point Likert scale ranging from 1 = "strongly disagree" to 7 = "strongly agree". The Chinese version of the NMP-Q was adapted using exploratory structural modeling (ESEM) and item response theory (IRT) by Ren, Gu-Li, and Liu (2020). The revised version of NMP-Q consists of 16 items measuring the same four dimensions as the original NMP-Q, and has also been shown to have good reliability (Ren et al., 2020). In the current study, the Cronbach's α for the total scale was 0.936 ($\omega = 0.936$, mean inter-item correlation [MIC] = 0.476), and the αs (MICs) for each of the four dimensions ranged from 0.822 to 0.908 (0.537–0.711) in the present study. All study participants completed this scale.

The generalized anxiety disorder 7-item scale (GAD-7). The GAD-7 (Spitzer, Kroenke, Williams, & Löwe, 2006) is a brief, reliable, and validated instrument used to screen for and identify the existence of anxiety disorders and assess symptom severity over the previous two weeks. This scale is a unidimensional tool consisting of 7 items. Each of the seven items is rated on a four-point Likert scale, with 0 = "not at all", 1 = "several days", 2 = "more than half the days", and 3 = "nearly every day". The GAD-7 provides an overall score that can range from 0 to 21. The cutoff of

this instrument is 10 with sensitivity of 86.2% and a specificity of 95.5% (Kroenke, Spitzer, Williams, Monahan, & Löwe, 2007). The GAD-7 has been validated in Chinese populations through several studies such as those conducted by Sun, Liang, Chi, and Chen (2021) and Tong, An, McGonigal, Park, and Zhou (2016). In the current study, the Cronbach's α was 0.887. Only Sample 1 completed this scale.

The Patient Health Questionnaire (PHQ-9). The PHQ-9 is the major depressive disorder subscale of the full Patient Health Questionnaire (PHQ; Kroenke, Spitzer, & Williams, 2001), and can be used to provisionally measure depression and grade symptom severity in general medical, mental health, and research settings. The PHQ-9 consists of nine items, each of which is scored on a four-point Likert scale in which 0 = "not at all", 1 = "several days", 2 = "more than half the days", and 3 = "nearly every day". A cutoff of 7 had a sensitivity and specificity of both 86% (Wang et al., 2014). The validity and utility of the Chinese version of the PHQ-9 in screening for depression has been demonstrated previously in studies involving Chinese adolescents (Leung, Mak, Leung, Chiang, & Loke, 2020) as well as the broader Chinese population (Wang et al., 2014). The Cronbach's α was 0.883 for the current study. Only Sample 1 completed this scale.

Statistical analysis. **Step 1: LPA.** LPA was conducted using M*plus* 8.3 to identify subgroups in Chinese college students who exhibited similar responses on the NMP-Q. Due to the non-normal distribution of our data (see Appendix 1), we employed robust maximum likelihood (MLR) with starting and ending values set at 200 and 50, respectively. As recommended by Tein, Coxe, and Cham (2013), the optimal model was selected based on the following indicators: the Akaike information criterion (AIC; Akaike, 1987), the Bayesian information criterion (BIC; Schwarz, 1978), the sample-size adjusted BIC (aBIC; Sclove, 1987), the bootstrap likelihood ratio test (BLRT; Mclachlan & Peel, 2004; Nylund, Asparouhov, & Muthén, 2007), the Lo-Mendell-Rubin test (LMR; Lo, Mendell, & Rubin, 2001), and entropy. Reduced values of AIC, BIC, and aBIC indicate an enhanced model fit. Entropy is a method for assessing the effectiveness of categorizing groups derived through LPA, with values ranging from 0 to 1. The closer the value is to 1, the more effective of the categorization. It is recommended to be equal to or larger than 0.8 (Fonseca-Pedrero, Ortuno-Sierra, de Albeniz, Muniz, & Cohen, 2017; Lubke & Muthén, 2007). BLRT and LMR were used for model comparison, with $p < 0.05$ indicating that the model with k profiles fit better than that with k-1 profiles (L. K. Muthén & B. O. Muthén, 2012). Furthermore, it is necessary to comprehensively consider the practical implications of the classification and sample size (>5%) included in each profile (Li et al., 2020; Nagin, 2005). Therefore, Cohen's d was computed to further verify the accuracy of the classification, with Cohen's d values of 0.2, 0.5, and 0.8 representing small, medium, and large effect sizes, respectively (Cohen, 1988; Fu, Si, & Guo, 2022).

Step 2. ROC analysis. To determine the optimal critical value for the NMP-Q, a combined method of LPA and ROC analysis was adopted (Bányai et al., 2017; Garrett, Eaton, & Zeger, 2002; Király et al., 2017; Li et al., 2020) utilizing the pROC package for R Version 22.0.3. The ROC is commonly used to assess and select an optimal cut-off value for a dichotomous diagnostic test. The indicators for evaluating the performance of classification models include true positive rate (TPR), false positive rate (FPR), positive predictive value (PPV), negative predictive value (NPV), accuracy, the area under the curve (AUC), and Youden's index. Higher TPR and lower FPR values indicate that the model can better identify true positive samples and avoid false positives, having high sensitivity and specificity. Additionally, higher PPV and NPV values mean that the model has stronger classification ability for positive and negative samples (Glaros & Kline, 1988). Indicator accuracy can reveal the overall classification accuracy. Meanwhile, the AUC is the area under the ROC curve, with values ranging from 0 to 1; the closer the values are to 1, the higher the prediction accuracy (Greiner & Gardner, 2000). The optimal benchmark is therefore typically identified based on the AUC and the maximum Youden's index value, as determined by TPR and FPR (Akobeng, 2007).

Step 3. Validity analysis of the optimal critical value. To validate the selected optimal cutoff point and determine the effectiveness of the NMP-Q in this study, chi-square values and odds ratios (*OR*s) were calculated to examine the relationships among reference groups, screening groups, and external variables (i.e., gender, anxiety, and depression).

Ethics

The current survey was approval by the Human Subjects Review Committee of Guizhou Normal University (GZNUPSY.N.202208E [0027]). All participants provided their written informed consent before participating, and were fully informed about the purpose and nature of the study. All were assured of the confidentiality and anonymity of their responses, as well as the voluntary nature of their participation. Participants were given the freedom to choose whether they would take part in the survey and had the option to withdraw at any point without consequence.

RESULTS

LPA results

Table 1 shows the LPA results from the one- to five- profile solution. Although all the values of LLs, AICs, BICs, and aBICs decreased consistently as the number of profiles increased, and all p-values of the LMRs and BLRTs were significant, the two-profile and three-profile models were determined to be the most likely candidates due to their higher entropy values compared to the four- and five- profile models (0.912 and 0.909, respectively).

Visual inspection of the scree plot (see Appendix 2) revealed an "elbow point" at the three-profile solution, indicating that the addition of a profile from 3 to 4 did not significantly improve the model fit, as the descent speed of aBIC from 3 to 5 was much slower than it was in going from 1 to 3. Figure 1 displays the two- and three-profile models

Table 1. Fit statistics for the latent profile analysis and the corresponding profile probability

Model	*k*	G^2/LL	AIC	BIC	aBIC	Entropy	*p*LMR	*p*BLRT	Profile Probability (%)
1-profile	32	−126,823.65	253,711.29	253,912.69	253,811.00	–	–	–	–
2-profile	49	−116,475.04	233,048.08	233,356.47	233,200.77	0.912	<0.001	<0.001	41.07/58.93
3-profile	66	−112,781.78	225,695.57	226,110.94	225,901.22	0.909	<0.001	<0.001	23.11/50.15/26.74
4-profile	83	−111,398.87	222,963.75	223,486.11	223,222.37	0.885	<0.001	<0.001	14.68/28.61/41.42/15.28
5-profile	100	−110,392.76	220,985.53	221,614.88	221,297.13	0.886	<0.001	<0.001	13.78/13.33/17.88/40.37/14.63

Note: *k* = number of free parameters; AIC = the Akaike information criterion; BIC = the Bayesian information criterion; aBIC = the sample-size adjusted BIC; BLRT = the bootstrap likelihood ratio test; LMR = the Lo-Mendell-Rubin test.

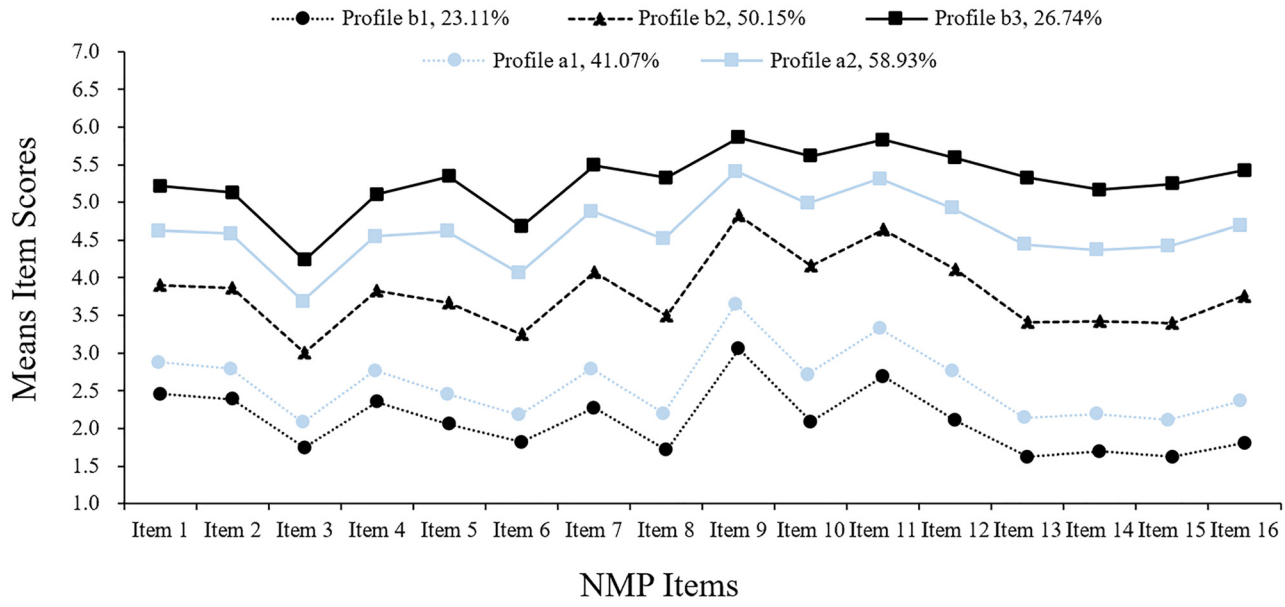

Fig. 1. Conditional mean for each profile based on the 2- and 3-latent profile
Note: The blue colors represent the 2-profile model with Profile a1 and Profile a2 (Model 1), while black signifies the 3-profile model with Profile b1, Profile b2, and Profile b3 (Model 2).

(two-profile model/Model 1: profile a1 and profile a2; three-profile model/Model 2: profile b1, profile b2, and profile b3), which were derived according to the NMP-Q responses received. The mean values of the two profiles in Model 1 were positioned between the mean values of Profiles b1 and b2, and also between the average values of Profiles b2 and b3 in Model 2. In other words, individuals with lower scores in Profile a1 were extracted to form Profile b1, and individuals with higher scores in Profile a2 were extracted to form Profile b3, while individuals with higher scores in Profile a1 and those with lower scores in Profile a2 were combined to form Profile b2. Furthermore, the average latent profile probabilities for the 3 profiles were 0.97, 0.96, and 0.95, respectively, and both those and the Cohen's *d* values (see Appendix 3) of the three-profile model were both higher than 0.80, demonstrated strong discrimination and classification accuracy. In consideration of the overall results, the three-profile model was chosen as the optimal model in the present study.

The three-profile model shown in Fig. 1 revealed that three subgroups exhibited similar patterns but varied in their levels, and as such were labeled "no-risk NMP" (23.32%), "low-risk NMP" (49.84%), and "at-risk NMP" (26.84%). Appendix 3 presents the descriptive information of the three-profile model.

ROC analysis results

Participants in no-risk NMP and low-risk NMP groups were recoded as 0 ("non-case" group), while those in the at-risk NMP group were re-coded as 1 ("case" group) during the ROC analysis. Table 2 presents the results of a Sensitive analysis, including sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), accuracy, and Youden's index. Based on these results, a threshold of 73 was determined as being the optimal cutoff point, as it yielded the highest Youden's index of 0.935. This threshold demonstrated a sensitivity of 0.965, specificity of 0.970, PPV of 0.921, NPV of 0.987, and accuracy of 0.968. The ROC curve (see Appendix 4) illustrated a substantial area under the curve (AUC) of 0.996 (95% CI: 0.994, 0.997; $p < 0.001$). This further supported the selection of the 73 thresholds. By applying this cutoff point, a number of 1,121 out of the total of 3,998 participants were identified as probable positive cases, with scores equal to or above 73,

Table 2. Critical values based on the at-risk of NMP group derived through latent profile analysis

Values	TP	FP	FN	TN	Sensitivity	Specificity	PPV	NPV	Accuracy	Youden's index
68	1,067	452	2	2,477	0.998	0.846	0.702	0.999	0.886	0.844
69	1,067	359	2	2,570	0.998	0.877	0.748	0.999	0.91	0.875
70	1,065	279	4	2,650	0.996	0.905	0.792	0.998	0.929	0.901
71	1,060	208	9	2,721	0.992	0.929	0.836	0.997	0.946	0.921
72	1,049	142	20	2,787	0.981	0.952	0.881	0.993	0.959	0.933
73	1,032	89	37	2,840	0.965	0.970	0.921	0.987	0.968	0.935
74	1,003	61	66	2,868	0.938	0.979	0.943	0.978	0.968	0.917
75	972	37	97	2,892	0.909	0.987	0.963	0.968	0.966	0.896
76	930	20	139	2,909	0.870	0.993	0.979	0.954	0.960	0.863
77	868	11	201	2,918	0.812	0.996	0.987	0.936	0.947	0.808

Note: TP = true positive; FP = false positive; FN = false negative; TN = true negative; PPV = positive predictive value; NPV = negative predictive value.

and based on that, a relatively conservative NMP proportion of 28.04% was determined.

The validity of the LPA and ROC analysis

First, to validate the effectiveness of the cut-off point of 73 for distinguishing participants with or without NMP, who exhibited correspondingly higher or lower responses across all dimensions of the NMP-Q, we conducted an analysis of participant performance across all four dimensions (see Fig. 2). The results indicated that the positive cases (scores ≥73) obtained higher scores ([19.89, 22.89]) across all four dimensions compared to the negative cases ([11.71, 15.12]). These differences in mean values between the two groups were statistically significant (*p*s < 0.05, Cohen's *d* values ranging from 1.55 to 1.93). Furthermore, participants from the different groups exhibited relatively higher scores on the FLC dimension compared to other dimensions, particularly those classified as at-risk NMP according to LPA, and as positive cases according to ROC analysis. Finally, upon combining these results with the findings from Appendix 3, it was evident that while the average total scores were similar between the at-risk NMP and Positive cases, there were clear identifying differences revealed through LPA and ROC analysis.

Therefore, to further explore the validity of the LPA and ROC analysis results, we compared the relationships between the various groups and external variables (i.e., gender, depression, and anxiety). Table 3 shows that participants classified into probable positive group when their scores were at or above 73 were more likely be female (*N* female = 829, $p < 0.001$; see Table 3), and had higher scores for anxiety and depression ($GAD_{mean} = 6.48$, $p < 0.001$, Cohen's $d = 0.56$; $PHQ_{mean} = 7.63$, $p < 0.001$, Cohen's $d = 0.60$; see Table 3). A significant relationship was also found between Positive and Negative cases with gender (*OR* = 1.74, 95% CI for OR: [1.49, 2.03]), GAD (*OR* = 2.64, 95% CI for OR: [1.93, 3.60]), and with PHQ (*OR* = 3.02, 95% CI for OR: [2.43, 3.76]). See Table 3 for more detailed information.

DISCUSSION

The current study aimed to determine an objective cut-off point of NMP among Chinese college students, as well as to determine the most likely proportion of NMP, with a

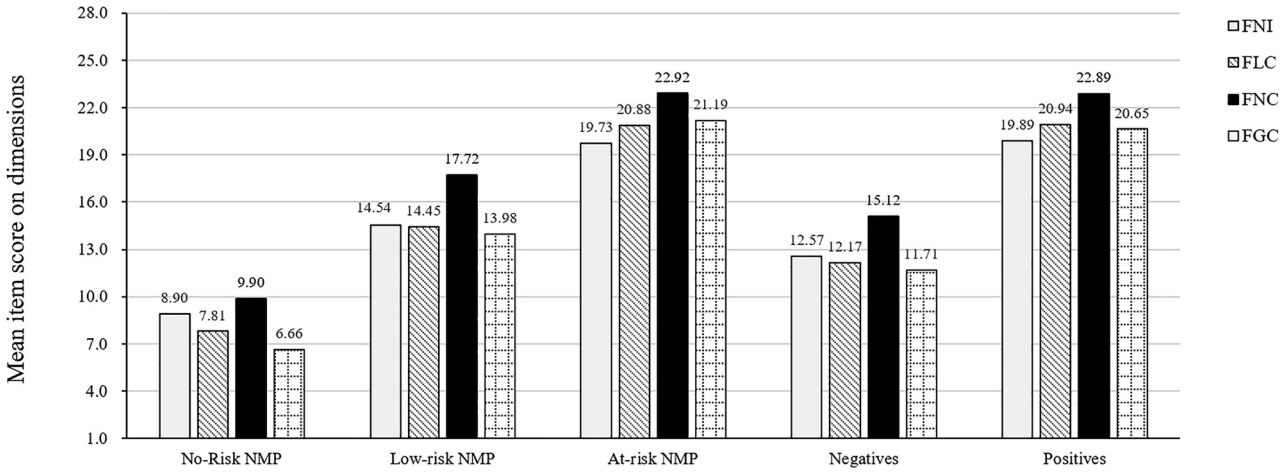

Fig. 2. Performance of different participants from latent profile and receiver operating characteristic analyses on four dimensions
Note: FNI = fear of not being able to access information; FLC = fear of losing connectedness; FNC = fear of not being able to communicate; FGC = fear of giving up convenience.

Table 3. Comparison of external variables between three latent profiles, and between positive and negative cases of nomophobia

Factors	The three latent profiles from LPA					NMP classification (cut-off ≥73 for positive cases)			
	No-risk NMP[a]	Low-risk NMP	At-risk NMP	*p*-values	Effect size	Positive cases	Negative cases	*p*-values	Effect size
Gender (N = 3,998)									
Male[a]	395	689	279	<0.001	$OR_{low\text{-}risk}$ = 1.42 [1.21, 1.67]	286	1,077	<0.001	OR = 1.74 [1.49, 2.03]
Female	528	1,311	784		$OR_{at\text{-}risk}$ = 2.10 [1.74, 2.54]	829	1,794		
GAD (N = 1,745)									
0–9 scores[a]	405	894	255	–	–	382	1,172	<0.001	OR = 2.64 [1.93, 3.60]
10–21 scores	0	0	186			86	100		
Mean (*SD*)	0.71 (0.71)	4.20 (1.51)	10.15 (3.62)	<0.001	η^2 = 0.88	6.48 (4.31)	4.31 (3.70)	<0.001	*Cohen's d* = 0.56
PHQ (N = 1,745)									
0–6 scores[a]	328	579	195	<0.001	$OR_{low\text{-}risk}$ = 2.33 [1.75, 3.09]	206	896	<0.001	OR = 3.02 [2.43, 3.76]
7–27 scores	77	316	246		$OR_{at\text{-}risk}$ = 5.37 [3.93, 7.34]	262	377		
Mean (*SD*)	3.90 (4.17)	5.71 (3.87)	7.61 (4.80)	<0.001	η^2 = 0.13	7.63 (4.78)	5.09 (4.03)	<0.001	*Cohen's d* = 0.60

Note: 0–9 scores = absence of GAD; 10–21 scores = presence of GAD; 0–6 scores = absence of PHQ; 7–27 scores = presence of PHQ; *p*-values were obtained by independent-sample *t*-test for two-group continuous variables and one-way ANONA for three-group continuous variables; Effect size: *OR* (i.e., odds ratio) for categorical variables and η^2 and Cohen's *d* for continuous variables. The upper right superscript "a" represents the reference group; The *p*-value and effect size for GAD with the three latent profiles from LPA could not be calculated due to two cells having a frequency of 0.

reasonable scope. LPA was used to detect three distinct latent profiles, and 26.84% of the study participants were classified as at-risk NMP (i.e., "case" group). ROC analysis determined a threshold of 73 as the optimal cut-off point for identifying probable positive cases (N = 1,121; 28.04%), with a high sensitivity of 0.965 and specificity of 0.970. The positive and negative cases exhibited differences in terms of gender, anxiety, and depression disorder, which suggested acceptable external validity. The identified cut-off points of 73 has the potential to be a valuable reference for future research in this field (Li et al., 2020).

The relatively conservative prevalence of NMP

The detection rate of NMP in the current sample was found to be 28.04%, according to the determined cut-off point, which is relatively conservative and in stark contrast to findings from previous studies. This could be that the proportion of NMP has been overrated in prior studies. For instance, the detection rate of NMP in European adolescents was found to be approximately 85% (Galhardo et al., 2023; González-Cabrera et al., 2017). Similarly, the NMP rate in Asian youth has also been shown to be significant, with Chinese college students reporting 82.9% (Ma & Liu, 2021) and Indian high school students reporting 68.02% (Sharma et al., 2019). Furthermore, a case-based meta-analysis reported that the overall incidence of NMP among university students reached nearly 100% (Tuco et al., 2023). These seemingly high NMP proportion may be attributed to several reasons. First, the disparity in scoring criteria extant studies employed is a significant influencing factor (Li et al., 2020). As NMP is a relatively new phenomenon which has emerged alongside the rapid technological advancements of the past decade, research in this area is still in the exploratory stages (Rodríguez-García, Moreno-Guerrero, & López Belmonte, 2020). As a result, the industry has not yet established a consistent standard for assessing NMP. As previously mentioned, the percentage of people with NMP based on varying criteria will exhibit large fluctuations. Second, the overrated NMP detection rate could simply be due to some scholars confusing the concepts of mobile dependency (MD) and NMP, and mistakenly interpreting MD measurements as an assessment of NMP (Argumosa-Villar, Boada-Grau, & Vigil-Colet, 2017; León-Mejía et al., 2021). As MD is quite a common phenomenon (e.g., Konok, Pogány, & Miklósi, 2017), the high incidence of MD may inadvertently amplify the detection rate of NMP. Numerous studies have in fact employed MD to elucidate NMP (e.g., Konok et al., 2017; León-Mejía et al., 2021), however, it is important to recognize that these two concepts are distinct and should be treated as such (King et al., 2010). Finally, the high proportion of NMP could be attributed to various methodological issues, such as convenience sampling which primarily targets students, sample sizes being small (Ko et al., 2009), or varying assessment scales (León-Mejía et al., 2021; Li et al., 2020).

It should be noted that during the preliminary stage of preparing the LPA to determine the critical value, the

selection of the optimal model is not definitive. And the identified threshold of 73 pertains only to an abbreviated Chinese version of the NMP-Q. It raises questions regarding its alignment with the cutoffs of the complete 20-item questionnaire as well as other NMP assessment tools. Therefore, caution should be taken when applying our NMP ratio into other situations or cultures. Together, this finding reminds us of the need for heightened attention to NMP and the development of specialized intervention plans to address this issue.

The validity of the selected cut-off point

This study also found that the selected cut-off point of 73 exhibited sufficient internal and external validity. First, based on the responses of each group on the NMP-Q, our findings indicate that individuals assigned to the Positive group achieved significantly higher scores on the entire scale and in all four dimensions compared to those in the Negative group, demonstrating that the selected cut-off point of 73 can not only be used to distinguish whether individuals do or do not have NMP, but it also potentially result in more reasonable and formalized scope of NMP incidence, and allow for comparison across studies and contexts. In addition, regardless of which group participants were assigned to, all reported the highest values in response to "fear of not being able to communicate (FNC)" when without their smartphones, which consistent with previous study results (Moreno-Guerrero, Aznar-Díaz, Cáceres-Reche, & Rodríguez-García, 2020; Yildirim et al., 2016). This points to the importance of maintaining contact with others for college students. As such, communication should be prioritized as a key intervention strategy for college students who are suffering from NMP. Second, individuals in the Positive group reported higher levels of anxiety and depression. Similar conclusions have been reached by previous studies in an analysis of the relationships between NMP and psychiatric symptoms (e.g., Galhardo et al., 2023; Kara, Baytemir, & Inceman-Kara, 2019; Kuscu, Gumustas, Rodopman Arman, & Goksu, 2021; Lee, Kim, Mendoza, & McDonough, 2018; Sharma et al., 2019). Positive correlations were found to exist between NMP and negative emotions such as anxiety, depression, and stress among Portuguese adolescents (Galhardo et al., 2023). It should be noted that anxiety is very common in college students as they experience pressures from various directions, such as academia, family, peers, employment, and more, and that individuals with pre-existing anxiety are more prone to transitioning towards NMP (Ayar, Özalp Gerçeker, Özdemir, & Bektaş, 2018; King et al., 2013). With this in mind, college students already experiencing higher levels of anxiety and depression will most likely also experience an elevated degree of NMP. Finally, our findings also reveal a higher detection rate of NMP among female college students compared to their male counterparts. This observation aligns with those of previous studies, such as one conducted in a similar context by Ma and Liu (2021), as well as with the findings of other relevant studies (Galhardo et al., 2023; León-Mejía et al., 2021; Moreno-Guerrero et al., 2020; Ramos-Soler, López-Sánchez, & Quiles-Soler, 2021). One potential explanation for this could be that females are more likely to experience negative emotions and develop smartphone addiction (SA; Fryman & Romine, 2021). SA and anxiety have been shown to have strong and significant positive correlations with NMP (Ayar et al., 2018; Konok et al., 2017). Studies have found that most women tend to experience appearance anxiety (Ayar et al., 2018) and feel unsafe in public places, but that smartphones can provide them with an "out" or a way to curb these feelings (Fryman & Romine, 2021). Therefore, to maintain their social media identities (Chen et al., 2017) and a sense of security by staying in touch with others through their smartphones, women tend to spend much more time on their smartphones than men.

Finally, it is worth noting that epidemiological studies on NMP have predominantly employed a variable-centered approach. While this methodology has its merits, it may not adequately capture the heterogeneity of individuals and may in fact overlook effects that are specific to certain subgroups (Gabriel, Daniels, Diefendorff, & Greguras, 2015). To address this limitation, a person-centered approach can offer valuable insights by considering individual characteristics (Gabriel et al., 2015). Therefore, the critical value of 73 as generated through LPA and ROC analysis in this study can be considered to be more objective and accurate compared to other varying benchmarks as mentioned above. In situations where patient evaluation necessitates the utilization of a critical value, but a predefined threshold is absent, the ROC method in tandem with the exploratory results of LPA can be a valuable alternative solution (Li et al., 2020). Moreover, this combined method enhances the utilization of the NMP-Q scale and can be extended to evaluate other scales.

Practical implications

As previously mentioned, conducting interviews with each new patient to screen for NMP is time-consuming and often unrealistic in clinical settings. The NMP-Q, with its diagnostic cut-off point, could serve as a suitable screening tool for NMP and can benefit future research. The implication of our findings and results are threefold. First, the critical value identified has the potential to standardize detection rates and reduce the possibility of over- or underestimation of NMP. Second, the selected cut-off point of 73 can help to identify college students with NMP and facilitate or enable future epidemiological studies, particularly those on a larger scale, as the NMP-Q makes it quicker and easier to more reliably identify and intervene in NMP among college students. Finally, this threshold can facilitate agreements between clinicians and investigators, and provide healthcare professionals with a means to communicate about and compare clinical cases.

Limitations and future directions

This study does have certain limitations. First, the non-random sampling of participants in the study may limit

the generalizability of the detection rate of NMP among college students. Future research should prioritize random sampling methods to improve the representativeness of the findings. Second, as NMP is still not included in the DSM-V, the NMP-Q should only be treated as a screening tool rather than a diagnostic tool. Therefore, the cutoff point of 73 should not be treated as a formal clinical diagnosis. Future studies should investigate our results in a clinical sample to assess the actual functional impairment associated with NMP. Third, strong relationships of NMP with GAD-7 and PHQ-9 may only capture limited specificity/distinction from GAD and MDD severity, Therefore, future studies should utilize techniques such as incremental validity or network analysis to examine their intricate connections and distinctions in greater detail. Fourth, high ROC results may be influenced by using the same scale for testing and classification, leading to potentially misleading PPV and NPV values due to actual disorder prevalence. Future research should validate results from ROC analysis by utilizing independent testing tools and bases for classification in clinical samples to ensure the reliability of the results. Finally, this study was a cross-sectional study; to predict behavioral and health outcomes, researchers should adopt longitudinal study designs in the future to evaluate the effectiveness of the NMP-Q and of the identified cutoff point.

CONCLUSION

Despite the aforementioned shortcomings, our research has achieved meaningful findings. First, our study shows that the past incidence of NMP has been overrated, and that a more accurate proportion measure is likely more around 28.04% of the Chinese college student populations. Moreover, our results show that probable positive cases exhibit higher levels of anxiety and depression, with a higher proportion of females observed in the positive group. Finally, the combined approach of LPA and ROC analysis can serve as an alternative solution to determining the cutoff point in situations where patient assessment necessitates the utilization of benchmarks, but predefined thresholds are absent.

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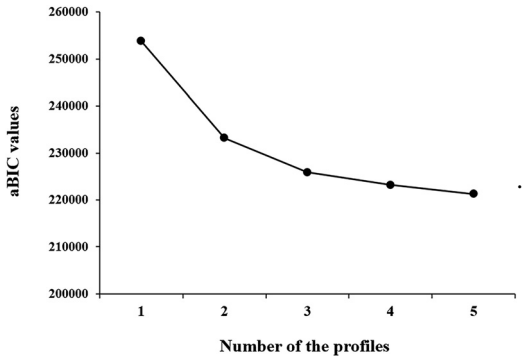
Appendix 1. The measures of central tendency and dispersion of scores on NMP-Q

	N (Missing)	Mean (*SD*)	Shapiro-Wilk	α (MIC)
Item 1	3,994 (4)	3.92 (1.77)	0.94***	0.46
Item 2	3,995 (3)	3.86 (1.71)	0.94***	0.64
Item 3	3,995 (3)	3.04 (1.62)	0.92***	0.47
Item 4	3,988 (10)	3.83 (1.72)	0.94***	0.60
Item 5	3,995 (3)	3.74 (1.90)	0.92***	0.55
Item 6	3,994 (4)	3.30 (1.85)	0.91***	0.47
Item 7	3,992 (6)	4.03 (1.87)	0.92***	0.53
Item 8	3,996 (2)	3.58 (1.83)	0.93***	0.65
Item 9	3,998 (0)	4.69 (1.74)	0.91***	0.64
Item 10	3,996 (2)	4.07 (1.75)	0.94***	0.75
Item 11	3,997 (1)	4.50 (1.76)	0.92***	0.74
Item 12	3,995 (3)	4.04 (1.72)	0.94***	0.65
Item 13	3,992 (6)	3.51 (1.72)	0.94***	0.72
Item 14	3,994 (4)	3.49 (1.72)	0.94***	0.72
Item 15	3,995 (3)	3.48 (1.72)	0.93***	0.77
Item 16	3,996 (2)	3.75 (1.80)	0.93***	0.62
F1	3,998	14.63 (5.51)	0.99***	0.82 (0.53)
F2	3,998	14.64 (6.05)	0.98***	0.83 (0.55)
F3	3,998	17.30 (6.11)	0.97***	0.90 (0.69)
F4	3,998	14.22 (6.14)	0.97***	0.91 (0.71)
NMP-Q	3,998	60.78 (20.08)	0.99***	0.94 (0.48)

Note: F1 = fear of being unable to access information (Items 1–4); F2 = fear of losing connection to Internet (Items 5–8); F3 = fear of losing contact (Items 9–12); F4 = fear of losing convenience (Items 13–16). ***$p < 0.001$. The αs for items 1–16 refers to the item-score reliability (Zijlmans, van der Ark, Tijmstra, & Sijtsma, 2018).

Appendix 2. A scree plot based on the number of aBIC from 1- to 5- profile



Note: We portraited aBIC's scree plot based on Yang's (2006) simulation study which found that aBIC was the information index with the highest classification accuracy when each category contains at least 50 subjects.

Appendix 3. Descriptive information for each profile based on the optimal three-latent profile

	M (*SD*)	*N* (%)	Score Rangs	Cohen's *d*
LPA				
No-risk NMP	33.28 (9.44)	924 (23.11%)	[16, 55]	d_{2-1} = 3.29
Low-risk NMP	60.70 (7.77)	2,005 (50.15%)	[40, 82]	d_{3-2} = 2.86
At-risk NMP	84.72 (9.47)	1,069 (26.74%)	[64, 112]	d_{3-1} = 5.44
ROC				
Negatives	51.59 (15.00)	2,877 (71.96%)	[16, 72]	
Positives	84.37 (9.35)	1,121 (28.04%)	[73, 112]	

Note: Individuals were classified into groups of no-risk NMP, low-risk NMP, and at-risk NMP based on their most likely latent profile membership; Cohen' s d_{2-1} refers to the standardized mean difference between low-risk NMP and no-risk NMP; Cohen' s d_{3-1} refers to the standardized mean difference between at-risk NMP and no-risk NMP; Cohen' s d_{3-2} refers to the standardized mean difference between at-risk NMP and low-risk NMP; Individuals scoring at and over 73 were identified as Positives, and the remaining as Negatives.

Appendix 4. ROC curve for the NMP-C for diagnosing NMP