12-2022

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Current Psychology (2022) 41:8410–8423
https://doi.org/10.1007/s12144-022-02881-x

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Multidimensional Profiles of Addictive Smartphone Use: A Latent Profile Analysis

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Accepted: 4 February 2022 / Published online: 27 May 2022

Abstract

Given that crucial psychological attributes of smartphone addiction have been studied in isolation from each other, we examined latent profiles of emotional distress (depression, stress, loneliness, and fear of missing out; i.e., FoMO); protective traits (self-control, mindfulness, grit); the behavioral inhibition system (BIS) and approach system (BAS; drive, reward responsiveness, and fun seeking) in relation to addictive smartphone use. We identified three distinctive profiles, using five fit statistics: AIC, BIC, adjusted BIC, an entropy, and LRT. The self-controlled, gritty, and mindful profile (22.7%) was characterized by heightened levels of self-control, grit, and mindfulness but lower levels of emotional distress, BIS, and BAS. The emotionally distressed profile (29.8%) was distinguished by elevated levels of depression, stress, loneliness, FoMO, and BIS, but relatively lower protective traits and BAS. Lastly, the approach sensitive profile (47.5%) corresponded to the normative group characterized by relatively higher BAS but mostly average levels of emotional distress and protective traits. When both global and pairwise comparisons between profiles were performed using Wald tests, we found that the self-controlled, gritty, and mindful profile was associated with significantly lower smartphone addiction tendencies than emotionally distressed or approach sensitive profiles, while the latter two did not differ from each other. These results still held when multiple covariates (age, sex, and income) were controlled for. Using a sophisticated person-centered approach, our findings underscore multidimensional psychological profiles that have different associations with smartphone addiction.

Keywords Emotional distress · Protective traits · Behavioral inhibition system (BIS) · Behavioral approach system (BAS) · Smartphone addiction · Latent profile analysis

Introduction

Smartphones offer a myriad of advantages, including easy access to information and improved communication and social connection. However, addictive smartphone use—characterized by excessive, uncontrolled use that impairs daily functioning (Kwon et al., 2013)—has been associated with repercussions such as anxiety, depressive symptoms, sleep disturbance, reduced work productivity, and poorer well-being (Demirci et al., 2015; Duke & Montag, 2017; Guo et al., 2020; Hartanto & Yang, 2016; Xie et al., 2018; Yang, Fu, et al., 2020; Yang, Wang, et al., 2020). Given these findings, a growing body of literature has identified either risk or protective factors of addictive smartphone use to inform appropriate prevention or intervention techniques. For instance, several studies have pinpointed the role of emotional factors—depressive symptoms (Elhai et al., 2018; Elhai et al., 2018; Elhai, Tiamiyu, et al., 2018); fear of missing out (FoMO; Elhai, Gallinariet al., 2020; Elhai, Rozgonjuk, et al., 2020; Elhai et al., 2020; Elhai et al., 2020; Wolniewicz et al., 2019); and loneliness (Shen & Wang, 2019)—in driving addictive smartphone behaviors. Others have hinted at psychological protective traits such as self-control (Berger et al., 2018; Kim et al., 2016) and mindfulness (Elhai et al., 2018a, b, c) as factors that attenuate smartphone addiction.

However, previous studies are limited in their ability to formulate a more organized and holistic perspective for individual differences associated with addictive smartphone use. This is because they have predominantly relied on a traditional variable-centered approach

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that focuses on the variability of only a single or limited factors and their unique effects on addictive smartphone use. Despite its utility, this approach fails to concurrently consider a wide range of individual-difference factors that are intricately linked to each other within an individual and do not operate in isolation in engendering addictive smartphone use. Further, the traditional method is unable to consider population heterogeneity—i.e., subpopulations of individuals with qualitatively different psychological characteristics—with respect to addictive smartphone use. Given this, it is important to understand how multidimensional individual-difference factors operate concurrently within an individual and how they contribute to forming heterogeneous subgroups that may manifest different degrees of smartphone addiction (Elhai et al., 2018; Elhai et al., 2018; Elhai, Tiamyu et al., 2018; Elhai, Gallinari et al., 2020; Elhai, Rozgonjuk, et al., 2020; Elhai et al., 2020; Elhai et al., 2020; Wolniewicz et al., 2019).

Given these methodological shortcomings, a more sophisticated and rigorous approach that can extend the traditional variable-centered approach is warranted. In this regard, a person-centered latent profile analysis (LPA; Wang & Hanges, 2010) is a useful method and is becoming increasingly popular in clinical and applied fields, because it allows us to consider intraindividual variation across a wide range of indicators in relation to particular distal outcomes. Despite the notable strength of LPA, however, few studies have used this method in relation to addictive smartphone use. For instance, Marmet et al. (2018) identified seven distinct profiles based on 14 indicators selected from three major domains of family background (e.g., parental separation and relations to parents); personality (e.g., neuroticism, aggression, sensation seeking); and mental health factors (e.g., bipolar disorder, social anxiety, stress). They demonstrated that distinct profiles were associated with different levels of behavioral addictions, including the internet, gaming, and smartphones, and highlight the need to examine intraindividual variations.

Using LPA, therefore, we sought to identify qualitatively discrete latent subgroups (i.e., typologies) based on their shared psychological profiles extracted from a host of multidimensional indicators that characterize emotional characteristics, protective personality traits, and dispositional behavioral sensitivity. Further, we sought to examine how these latent profiles are differentially associated with addictive smartphone use. Below, we elaborate on theoretically and empirically important psychological attributes—which served as indicators to extract latent profiles—across three major domains of emotional distress (depression, stress, loneliness, FoMO); protective traits (self-control, grit, mindfulness); and dispositional behavioral sensitivity (i.e., inhibition/activation system).

Emotional Distress

Depression and Stress The Compensatory Internet Use Theory (CIUT; Kardefelt-Winther, 2014) postulates that problematic internet technology use—which includes smartphone use—is a maladaptive strategy by which people regulate aversive emotions. Accordingly, individuals who are chronically depressed or stressed are more susceptible to addictive smartphone use to temporarily relieve depressive mood (Kim et al., 2015) or stress (Wang et l., 2015). Attesting to this, the severity or risk of excessive smartphone use have been shown to be associated with symptoms of both depression (e.g., Demirci et al., 2015; Kim et al., 2017) and stress (e.g., Chiu, 2014; Cho et al., 2017; Samaha & Hawi, 2016; Yang et al., 2021). Moreover, Sim et al. (2016) found that college students' stress levels influenced their degree of smartphone addiction via depression as a key mediator. Both theoretical perspectives and empirical results suggest that depression and stress are important psychological factors that characterize addictive smartphone use.

Loneliness Given that loneliness constitutes perceived deficiencies in one's ongoing social relations (Peplau et al., 1979), there is heightened risk that lonely individuals engage in more excessive smartphone use because it provides immediate ways to seek social satisfaction and alleviate loneliness (Bian & Leung, 2014). In line with this, a wealth of studies demonstrate that higher levels of loneliness in college-aged adults are predictive of smartphone overuse (Shen & Wang, 2019; Tan et al., 2013), which underpins loneliness as a key psychological indicator of addictive smartphone use. *FoMO.* FoMO refers to feelings of fear, worry, and anxiety when absent from rewarding experiences or conversations that are taking place across one's social circles (Przybylski et al., 2013). Given that individuals with higher levels of FoMO are anxious about missing pleasurable experiences and have a constant need for social connection, they are prone to overuse their smartphones to satisfy this need (Elhai et al., 2016, 2018, 2018; Elhai, Tiamiyu, et al., 2018). Supporting this notion, numerous studies have shown that the extent to which young adults experience FoMO predicts the severity of addictive smartphone use (Elhai et al., 2020a, d, 2018a, Wolniewicz et al., 2019). Taken together, it is reasonable to believe that these emotional distress factors (depression, stress, loneliness, and FoMO) would characterize crucial aspects of the psychological profiles of addictive smartphone users.

Protective Traits

Self-Control Given that addictive smartphone use involves the failure to refrain from excessive smartphone use (Jeong et al., 2016; Kwon et al., 2013), poorer self-control—i.e., the control over impulses in pursuit of long-term goals (Tangney et al., 2004)—likely constitutes an important aspect of addictive smartphone use. Similarly, the social control theory (Hirschi, 1969) and framework of behavioral addiction (Brown, 1993, 1997) postulate that smartphone addiction may stem from one's failure to control growing impulses for smartphone engagement. In line with this, low levels of self-control have been linked to higher frequencies of smartphone use (Wilmer & Chein, 2016); excessive mobile phone use in females (Jiang & Zhao, 2017); immediate responses to smartphone notifications (Berger et al., 2018); and greater risk of smartphone addiction (Khang et al., 2013; Kim et al., 2016). These findings suggest that self-control serves as a vital factor that protects against addictive smartphone use.

Grit Grit entails consistent interests and effort to accomplish long-term goals, even when faced with failure and adversity (Duckworth et al., 2007). Since grit is closely tied to perseverance and self-control, it is theorized that grittier individuals are better able to delay gratification and cope adaptively, and are thus less likely to rely on maladaptive coping strategies such as smartphone overuse (Guerrero et al., 2016; Yoo & Choi, 2019). While there is a paucity of research on the relation between grit and smartphone addiction, a handful of studies have found that grit serves to protect against excessive smartphone use (Kim et al., 2021; Yoo & Choi, 2019). Thus, these findings suggest that it is important to delineate individual differences in girt in the context of addictive smartphone use.

Mindfulness Mindfulness entails the regulation of one's attention to focus on the present moment while adopting a curious, open, and accepting orientation toward immediate experiences (Bishop et al., 2004). Mindfulness can be conceptualized as cognitively less demanding strategies to regulate emotion through emotional awareness and nonjudgmental engagement, which can lead to more adaptive behaviors (Chambers et al., 2009). In line with this, Kang et al. (2013) demonstrated that both mindfulness and reappraisal were effective in regulating sadness, but mindfulness implicated less depletion of cognitive resources than reappraisal. Given that mindful practices facilitate emotional coping and can ease individuals' reliance on smartphone use to avoid maladaptive and aversive emotions, prior studies indicate that mindfulness is associated with lower tendencies for problematic smartphone (Elhai et al., 2018; Elhai et al., 2018; Elhai, Tiamiyu, et al., 2018) and internet use (Arslan, 2017). Further, higher trait mindfulness has been shown to attenuate relations between affective factors—such as depression (Yang et al., 2019) and perceived stress (Liu et al., 2018)—and addictive smartphone behaviors. In sum, accumulated evidence regarding self-control, grit, and mindfulness highlights the beneficial roles of these protective traits in attenuating addictive smartphone use.

Dispositional Behavioral Sensitivity

Reinforcement sensitivity theory (Carver & White, 1994; Gray, 1981) postulates that the behavioral activation system (BAS) and behavioral inhibition system (BIS) govern human behavior via distinct dispositional sensitivities to either rewarding or aversive stimuli (Gray, 1981; Gray & McNaughton, 2000). While the BAS responds to reward signals with positive approach behaviors, the BIS responds to punishment signals with withdrawal or avoidance behaviors (Gray, 1981). Numerous studies suggest that BAS and BIS are important behavioral factors that contribute to addictive behaviors, including smartphone and substance overuse (Franken & Muris, 2006; Jeong et al., 2020; Johnson, 2003; Kim et al., 2016). Specifically, studies have consistently shown that higher BAS has been linked to smartphone and internet addiction tendencies in adults (Kim et al., 2016; Yen et al., 2008). However, findings regarding the relation between BIS and smartphone addiction are mixed. On one hand, higher BIS may buffer against addiction by reducing impulsive and risk-taking approach behaviors, including substance abuse (Franken & Muris, 2006) and problematic smartphone use in young adults (Jiang & Zhao, 2017). On the other hand, heightened sensitivity to signals of punishment in daily life may exacerbate addictive behaviors, including excessive internet use (Yen et al., 2008) and computer overuse (Giles & Price, 2008), because they alleviate negative emotions. Therefore, although not conclusive, it is essential that we view BIS/BAS as pertinent factors that could delineate important psychological characteristics of addictive smartphone use.

The Present Study

Since it was impossible to determine the number of profiles a priori, we set three major research objectives instead of forming specific hypotheses. First, we sought to determine the number of well-differentiated latent profiles based on multidimensional psychological factors of smartphone addiction across domains of emotional distress (depression, stress, loneliness, FoMO); protective traits (self-control, mindfulness, grit); and dispositional behavioral sensitivity (BIS, BAS-drive, -reward responsiveness, and -fun seeking). Our second objective was to investigate how these three psychological dimensions would form latent profile patterns.

Identifying psychological characteristics that specify each profile would shed light on understanding the concurrent operation of multiple psychological indicators that are intricately connected with each other. Our third objective was to investigate the association between qualitatively distinct latent profiles (subgroups) extracted from multidimensional psychological indicators and smartphone addiction (for our conceptual model, see Fig. 1). In all analyses, we controlled for important demographic covariates (age, sex, and income).

Methods

Participants

Two hundred and seven college students (M_{age} = 20.79 years; *SD* = 1.88 years; male = 28%) were recruited from a private university within a metropolitan area in Singapore and participated in the study in exchange for either course credit or a monetary reward ($5).

Measures

Smartphone Addiction

All survey questionnaires were written in English and administered using English instruction. The 10-item smartphone addiction scale (SAS-short version) was used to assess the extent of smartphone addiction as a distal outcome (e.g., missing planned work due to smartphone use; Kwon et al., 2013). The measure showed good reliability (α = 0.88). All items were rated based on a 5-point scale (1 = *Never*, 5 = *Very often*); higher scores denote higher levels of addictive smartphone use.

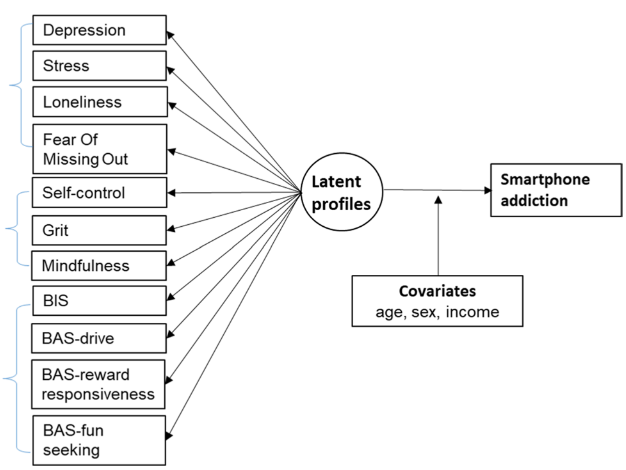

Fig. 1 Conceptual model illustrating the relation between the latent profile of multidimensional psychological indicators and smartphone addiction. Age, sex, and income served as covariates in estimating the relation between latent profiles and outcomes. Note that directional arrows do not imply causal relations. BIS = Behavioral Inhibition System. BAS = Behavioral Activation System

Emotional Distress

As indicators of emotional distress, we focused on depression, stress, loneliness, and fear of missing out (FoMO). Depression (7 items; α = 0.89; e.g., "I couldn't seem to experience any positive feeling at all") and stress (7 items; α = 0.82; e.g., "I found it hard to wind down") were assessed using corresponding subscales of the Depression Anxiety Stress Scales (DASS-21; Lovibond & Lovibond, 1995) on a 4-point rating scale (1 = *Not applicable;* 4 = *Applicable to me most of the time*); note that we did not use the anxiety subscale, since we were interested in social anxiety in particular, which was assessed by the FoMO scale. Items were summed such that higher scores indicate more symptoms of depression and stress.

Loneliness was assessed using the 6-item short-form De Jong Gierveld Loneliness Scale (α = 0.88; De Jong Gierveld & Van Tilburg, 2006). Participants rated their loneliness on a 5-point scale (1 = *Not at all like me*, 5 = *Very much like me*; e.g., "I experience a general sense of emptiness"). Summed scores were computed after reverse scoring selected items such that higher scores indicate greater loneliness.

Lastly, we employed a widely used 10-item scale (α = 0.88; Pzybylski et al., 2013) to assess FoMO, a form of social anxiety that has been shown to be associated with smartphone use (e.g., Elhai et al., 2020; Elhai et al., 2020; Elhai, Gallinari, et al., 2020; Elhai, Rozgonjuk, et al., 2020). Participants rated each statement on a 5-point scale (1 = *Not at all true for me*, 5 = *Extremely true for me*; e.g., "I fear that others have more rewarding experiences than me") and their responses were summed, with higher scores indicating a greater extent of FoMO.

Protective Traits

Three scales were used to assess aspects of protective personality traits: self-control, grit, and mindfulness. The 13-item brief self-control scale was employed to measure individual differences in trait-level self-control (α = 0.51; e.g., "I am good at resisting temptation"; Tangney et al., 2004). After reverse scoring some items, a summed score was used to index self-control, with higher scores indicating greater tendency for self-control.

Grit was assessed using the 8-item short-version scale (Duckworth & Quinn, 2009), which contains subscales for consistency (4 items; α = 0.80; e.g., "New ideas and projects sometimes distract me from previous ones") and perseverance (4 items; α = 0.75; e.g., "Setbacks don't discourage me"). Summed scores were computed after reversing consistency items, such that higher scores indicate greater grit.

We assessed mindfulness using selected subscales from the Five Facet Mindfulness Questionnaire (FFMQ; Baer et al., 2006). The Observing facet (7 items; "attending to internal feelings and external stimuli") may not fit into an overarching mindfulness construct (Baer et al., 2006), since it is differentially related to psychological adjustment, depending on one's meditation experience (Baer et al., 2008). Therefore, we focused on the four remaining FFMQ subscales: Describing (7 items; α = 0.81; e.g., "labeling feelings and experiences with words"); Acting with awareness (7 items; α = 0.86; e.g. "attending to the happenings in the present"); Non-judging of inner experiences (7 items; α = 0.91; e.g., "taking a non-evaluative stance toward internal feelings and experience"); and Non-reactivity to inner experience (7 items; α = 0.80; e.g. "allowing emotions and thoughts to come and go, not being interfered with by them"). Participants responded on a 5-point Likert scale (1 = *Never or very rarely true*, 5 = *Very often or always true*), with higher scores indicating higher levels of mindfulness.

Dispositional Behavioral Sensitivity

The 20-item behavioral inhibition/activation sensitivity (BIS/BAS) scale was used to assess the dispositional sensitivity of behavioral activation (approach) and inhibition (avoidance) systems that are thought to regulate appetitive and aversive motives at the personality level (1 = *Very true for me*, 4 = *Very false for me*; Carver &White, 1994). The overall measure consists of a single BIS scale (i.e., responsiveness to aversive stimuli; 7 items; α = 0.81) and three BAS scales: Reward Responsiveness (i.e., positive responses to reward; 5 items; α = 0.72); Drive (i.e., persistent pursuit of desired goals; 4 items; α = 0.74); and Fun Seeking (i.e., a desire to approach a rewarding occurrence on the spur of the moment; 4 items; α = 0.64). Each subscale score was averaged, such that higher scores indicate greater levels of BIS/BAS.

Covariates

We controlled for age, sex, and household income as covariates. Income was reported on a 9-point scale (1 = *Less than $2,500*, 9 = *More than $20,000*) at intervals of $2,500.

Results

Analytic Approach

Mplus 8.4 with full information maximum likelihood estimation was used to run all latent profile analyses (LPA; Muthén & Muthén, 2015). Descriptive statistics are shown in Table 1 (see Appendix 1 for zero-order correlations between all variables). We found no outliers when we conducted outlier analysis using the 3 IQR (interquartile range)

Table 1 Descriptive Statistics of Smartphone Indicators, Outcome Variables, and Covariates

	M	SD	Range	Skewness	Kurtosis
Age	20.79	1.88	19–27	0.29	-0.87
Sex (% male)	28%	-	-	-0.99	-1.04
Income[1]	3.75	2.45	1–9	0.73	-0.42
Depression	13.07	4.96	7–28	0.79	0.01
Stress	14.31	3.72	7–27	0.75	0.19
Loneliness	15.51	4.78	6–30	0.36	0.09
Fear of missing out	25.25	8.28	10–50	0.45	-0.20
Self-control	36.53	7.74	16–57	0.15	0.08
Mindfulness	85.59	13.25	47–123	-0.09	0.14
Grit	24.92	4.77	8–39	0.01	0.95
Behavioral inhibition system	22.06	3.69	10–28	-0.49	-0.29
Behavioral activation system-drive	11.09	2.11	6–16	0.33	-0.12
Behavioral activation system-reward responsiveness	16.82	2.21	11–20	-0.46	-0.45
Behavioral activation system-fun seeking	12.05	2.14	7–16	-0.08	-0.44
Smartphone addiction	26.04	8.15	12–50	0.47	-0.44

Note. Income was reported on a 9-point scale (1 = *Less than $2,500*, 9 = *More than $20,000*) at intervals of $2,500. Percentages of people within each income category are as follows: 1 = 22.7%; 2 = 15.5%; 3 = 14.5%; 4 = 15%; 5 = 10.6%; 6 = 6.3%; 7 = 4.3%; 8 = 3.4%; 9 = 7.7%.

rule, which allows us to detect extreme values that are three times greater than IQR values (Hoaglin & Iglewicz, 1987).

To examine the relations between latent profiles and smartphone addiction as a distal outcome while controlling for covariates, we employed Vurmunt's (2010) corrected three-step procedure since it provides unbiased estimates of the class-specific means of a distal outcome and allows for relatively greater flexibility to add and interpret covariates while taking into account classification errors (Bakk & Vermunt, 2016). Further, the corrected three-step procedure was shown to be more efficient and yield smaller standard errors for the covariates than the BCH approach (Bolck et al., 2004). In the first step, we established the latent profile model, without any distal outcome, using 11 indicators to depict multidimensional psychological characteristics of addictive smartphone use—depression, stress, loneliness, FoMO, self-control, mindfulness, grit, BIS, and three facets of BAS (drive, reward responsiveness, and fun seeking). Using standardized scores of indicators, we determined the number of profiles, starting from a two-class (profile) model and increasing its number until model fit no longer improved (Nylund et al., 2007). We used five fit statistics to evaluate the model fit of each profile model: the Akaike information criterion (AIC); Bayesian information criterion (BIC; Nylund et al., 2007); sample-size-adjusted BIC (aBIC; Tofighi & Enders, 2008); Lo-Mendell-Rubin likelihood ratio test (LRT; Lo et al., 2001; Tofighi & Enders, 2008); and entropy (see Table 2). The best-fitting profile model was determined by smaller AIC, BIC, and aBIC statistics; an entropy value greater than 0.80 (ranges from 0.00 to 1.00; Jung & Wickrama, 2007; Nylund-Gibson & Masyn, 2016); and a significant LRT statistic, which compares the fit of the k-profile model with the k—1 profile model (Berlin et al., 2013; Lo et al., 2001).

In the second step, we determined class memberships by assigning individuals to latent classes (profiles) using their posterior probabilities. In the final step, we tested an auxiliary model in which smartphone addiction and covariates (age, sex, and income) were added to the profile model as a distal variable and covariates, respectively, while taking into account the classification errors introduced in the second step. Then, we used Wald tests to examine whether the mean scores of smartphone addiction across the three profiles (subgroups) are significantly different while controlling for covariates.

Latent Profile Analysis

When we evaluated several profile solutions (see Table 2 for fit statistics), we found that AIC and aBIC values decreased progressively from the 2- to 4-class models, while BIC did not decrease further from the 4- to 5-class model, which suggests that the 5-class model does not contribute to forming a qualitatively new profile. Further, in line with the recommendation by Nylund et al. (2007), we found that an elbow point (i.e., the last relatively large decrease across AIC, BIC, and aBIC values) occurred with the 3-class model, suggesting that decreases in those model fit indices were stabilized in the 4-class model onward (Nylund-Gibson et al., 2014). Similarly, the LRT tests were statistically significant up to the 3-class model, $ps < 0.05$, but not for the 4- and 5-class models, $ps > 0.23$, which suggests that the 4- and 5-class models did not significantly differ from the 3-class model. The 3-class model had an acceptable entropy value of 0.86 and mean classification probabilities ranged from 0.91 to 0.96, which indicates reliable separation between profiles (Asparouhov & Muthén, 2014). Taken together, we chose the 3-class model as the best-fitting model (see Fig. 2).

Specifically, our first class (22.7% of participants), which was labeled a *self-controlled, gritty, and mindful* profile, was characterized by heightened levels of self-control, grit, and mindfulness and lower levels of emotional distress, BIS, and BAS (approach sensitivity). The second class (29.8%) was labeled an *emotionally distressed* profile and was distinguished by pronounced emotional distress (high depression, stress, loneliness, and FoMO) and elevated BIS (aversive/withdrawal sensitivity), but weaker protective traits. Lastly, the third class (47.5%) was labeled an *approach sensitive profile*, whose primary psychological characteristics were depicted by relatively higher levels of BAS (drive, reward

Table 2 Latent Profile Enumeration Fit Statistics for the 2-, 3-, 4-, and 5-class Models

	2-class	3-class	4-class	5-class
AIC	6,017.95	5,972.12	5,894.14	5,854.99
BIC	6,221.26	6,125.42	6,087.44	6,088.28
aBIC	6,113.54	5,979.67	5,903.67	5,866.49
Entropy	0.83	0.86	0.86	0.88
Model comparison	Class 1 vs. 2	Class 2 vs. 3	Class 3 vs. 4	Class 4 vs. 5
LRT statistics	404.55**	157.38*	100.41	62.18
p values	0.008	0.014	0.429	0.239

Note. AIC = Akaike information criteria; BIC = Bayesian information criteria; aBIC = Sample-size adjusted Bayesian information criteria; LRT = Lo-Mendell-Rubin likelihood ratio test.

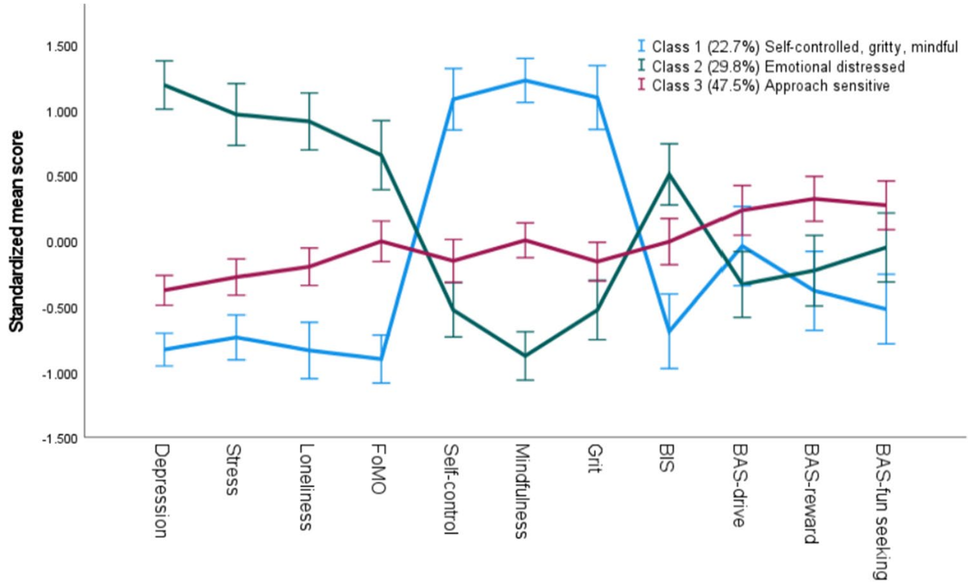

Fig. 2 Three latent profiles across 11 psychological indicators: depression, stress, loneliness, FOMO, self-control, mindfulness, grit, BIS, three facets of BAS (drive, reward responsiveness, and fun seeking). Error bars indicate ± 2 standard error (SE) of the mean. FoMO = fear of missing out; BIS = behavioural inhibition system; BAS = behavioural activation system

responsiveness, and fun seeking) but moderate levels of emotional distress and protective traits. It is noteworthy that the approach sensitive profile likely represents a normative group that comprises the largest class and whose mean scores of most indicators are close to the corresponding average scores of the entire sample.

As additional analyses, we examined whether the three profiles were significantly different from each other across 11 indicators. We found significant overall profile differences across all 11 indicators, all F statistics < 0.05. More specifically, the three profiles were significantly different from each other on most indicators except for BAS-drive and -reward responsiveness. Regarding BAS-drive, we found that only the emotionally distressed profile significantly differed from the approach sensitive profile whereas the self-controlled, gritty, and mindful profile did not differ from the other two profiles. Similarly, regarding BAS-reward responsiveness, we found that the approach sensitive profile significantly differed from the other two profiles, but the self-controlled, gritty, and mindful profile did not differ from the emotionally distressed profile. These findings suggest that BAS-drive and –reward responsiveness are relatively less salient indicators that uniquely differentiate the three profiles (see Table 4 in Appendix 2).

Smartphone Addiction

Lastly, we examined whether there are significant differences in the extent of smartphone addiction between the three psychological profiles when the influence of covariates was controlled for. Due to the probabilistic nature of profile membership, we conducted Wald tests for global comparison of the three profiles. Once the Wald test was found to be significant, we conducted further pairwise comparisons between profiles (see Fig. 3).

We examined whether the three profiles of psychological qualities would be differentially associated with smartphone addiction when age, sex, and income as covariates were controlled for. We found significant differences between latent profiles, $W(2) = 101.91$, $p < 0.001$. When pairwise comparisons between profiles were performed, we found that the self-controlled, gritty, and mindful profile showed significantly lower smartphone addiction than the emotionally distressed profile, $t = -8.767$, $p < 0.001$, and the approach sensitive profile, $t = -10.637$, $p < 0.001$. However, the emotionally distressed profile did not differ from the approach-sensitive profile, $t = -1.871$, $p = 0.366$. These results remained the same after Bonferroni correction for multiple comparisons. None of the covariates were significant, all ps > 0.12.

General Discussion

Using a sophisticated latent profile analysis, we examined the relations between heterogeneous psychological profiles and smartphone addiction tendency. We identified three latent profiles characterized by varying degrees of emotional

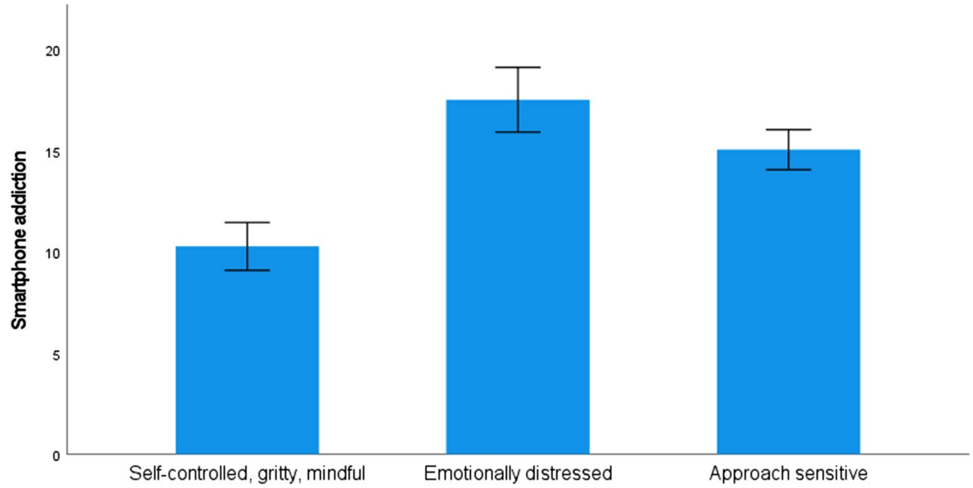

Fig. 3 Differences in smartphone addiction between latent profiles. The error bars represent ± 2 standard error (SE) of the mean

distress, protective traits, and behavioral dispositional sensitivity. We found that individuals whose psychological profile was distinguished by higher levels of protective traits (self-controlled, gritty, and mindful) and lower levels of emotional distress and BIS/BAS showed significantly lower risk for smartphone addiction than those whose psychological profiles were characterized by relatively higher levels of either emotional distress or the BAS.

Our findings are congruent with the pathway model of problematic mobile phone use, which posits that individuals have different predispositions toward smartphone addiction (Billieux et al., 2015; Pivetta et al., 2019). According to this model, three prevailing pathways lead to smartphone addiction—excessive reassurance, impulsive, and extraversion—each of which is associated with unique risk factors. Below, we discuss the theoretical and empirical parallels between psychological risk factors posited by the pathway model and our findings.

First, regarding the *excessive reassurance pathway*, the theory posits that individuals who are highly neurotic, emotionally unstable, and socially anxious would fall into problematic smartphone use (Billieux et al., 2015). Our findings attest to this by demonstrating that individuals with an emotionally distressed profile—who were emotionally susceptible (depressed, stressed, lonely, fearful of missing out) and reacted poorly to anticipated punishment (i.e., high BIS)—showed significantly higher risk for smartphone addiction than those with a self-controlled, gritty, and mindful profile whose emotional distress was kept at lower levels. This suggests that individuals with an emotionally distressed profile likely cultivate an unhealthy reliance on smartphones to quickly gratify their psychological need for social reassurance and alleviate their emotional distress (Elhai et al., 2020; Elhai et al., 2020; Elhai, Gallinari, et al., 2020; Elhai, Rozgonjuk, et al., 2020). Our findings corroborate other studies that have found that individuals who are depressed and socially anxious tend to ruminate about their problems and fall prey to excessive smartphone use for dysfunctional coping, such as mental disengagement from problems (Elhai et al., 2018; Elhai et al., 2018; Elhai, Tiamiyu, et al., 2018; Khoo & Yang, 2021). Furthermore, individuals who are high in FoMO are sensitive to punishment (e.g., being excluded from social groups) and thus could maladaptively resort to smartphones to alleviate post-punishment negative affect. These findings are also in line with predictions of the Compensatory Internet Use Theory (Kardefelt-Winther, 2014).

Next, Billieux et al. (2015) argue that individuals who are lacking in self-control and premeditation tend to adhere to the *impulsive pathway*. In favor of this, we found that individuals whose profile was characterized by higher levels of self-control, grit, and mindfulness showed the least proneness to smartphone addiction. Consistent with our findings, past studies have indicated that individuals who have high self-control are least likely to respond immediately to smartphone notifications (Berger et al., 2018). Also, lowered sensitivity to smartphone notifications is associated with reduced risks of smartphone addiction (Kim et al., 2016; Lee et al., 2014). Studies have also shown that mindfulness serves as a further protective trait in the link between depression and anxiety and unhealthy reliance on smartphones (Elhai et al., 2018; Elhai et al., 2018; Elhai, Tiamiyu, et al., 2018; Yang et al., 2019). Given that grittier individuals tend to push through setbacks to experience satisfactory achievement of success and are better at adaptive coping (Blalock et al., 2015), they are less likely to depend on maladaptive smartphone use to cope with stress. Taken together, our findings extend previous findings on the instrumentality of these protective personality traits with respect to smartphone addiction.

Lastly, the *extraversion pathway* of Billieux et al.'s (2015) model posits that highly extraverted individuals who seek sensations and rewards (the approach sensitive profile) are prone to addictive smartphone use. We similarly found that individuals who scored high on all facets of BAS (i.e., drive, reward, fun seeking) were as much inclined to smartphone addiction as those who were emotionally distressed. Past studies have highlighted BAS as being positively associated with substance use (Franken, 2002; Franken & Muris, 2006; Yen et al., 2009) and smartphone addiction (Jeong et al., 2020; Kim et al., 2016). Given that smartphones are highly stimulating and offer numerous sources of entertainment and pleasure, it is not surprising that individuals who are especially sensation-seeking and attracted to rewards would find themselves constantly drawn to their smartphones. In favor of this, one study showed that smartphones' value-added functions (e.g., communication and entertainment services) served to increase one's perceived enjoyment in a positively reinforcing manner, thereby leading to heightened smartphone addiction (Chen et al., 2019).

Our study is not without limitations. First, our cross-sectional design emphasizes associations between latent profiles of multidimensional psychological indicators and smartphone addiction, but restricts any conclusive causal explanations or interpretations of directionality. Therefore, more sophisticated longitudinal studies are required to ascertain the directionality of relations between these profiles and smartphone addiction. Second, our sample size is considered small; thus, it is vital to replicate our findings with a larger and more representative sample. Nevertheless, given that our fit indices were favorable, proportions of the three classes were relatively well balanced, and we did not encounter convergence failures, our sample size can be acceptable although not optimal. In line with this, Nylund et al. (2007) maintained that although a larger sample is generally recommended for LPA, smaller samples can be acceptable in models with fewer indicators and classes that are clearly distinguishable. Third, our sample consisted of college students, and thus our findings may not be generalizable to other populations (e.g., children, adolescents, and older adults) whose developmental psychological characteristics may be unique and distinguished from those of young adults. Future studies should therefore involve more representative and diverse samples to replicate these profiles in other populations and examine their links to smartphone addiction. Fourth, our study focused on 11 psychological factors of emotional distress, protective traits, and dispositional behavioral sensitivity, which have been shown to either protect against or exacerbate addictive smartphone use. It is notable, however, that there are other crucial factors, such as anger (Elhai et al., 2019; Khoo & Yang, 2021) and psychopathic traits (e.g., narcissism, spitefulness; Balta et al., 2019), that can contribute to the formation of heterogeneous profiles that are associated with addictive smartphone use. Thus, further research is warranted to more clearly delineate heterogeneous profiles based on a wide array of psychological attributes (factors) for addictive smartphone use.

Taken together, by using a sophisticated latent profile analysis, our study emphasizes the differential associations between heterogeneous profiles of multidimensional psychological indicators with addictive smartphone use in young adults. Our findings extend existing theoretical understanding of the individual difference factors of smartphone addiction and highlight the need to pay more attention to smartphone users' discrete psychological profiles in examining individual differences for addictive smartphone use. Further, the consideration of multidimensional indicators in our study extends understanding of the concurrent operation of various individual difference factors in relation to varying degrees of risk for smartphone addiction. Moreover, our findings carry important practical implications, in that appropriate prevention or intervention techniques for smartphone addiction should target the specific psychological dimensions that drive smartphone addiction in light of an individual's heterogeneous psychological profile. For instance, those whose profiles are characterized by high emotional distress may require stronger social support to improve emotion regulation as an effective intervention strategy to reduce emotional insecurity and reliance on addictive smartphone use.

Appendix 1

Table 3 Bivariate Zero-order Correlations among All Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Age	-													
2. Sex	-0.545*	-												
3. Income	-0.121	0.020	-											
4. Depression	0.092	-0.102	0.006	-										
5. Stress	0.130	-0.045	0.040	0.716**	-									
6. Loneliness	0.075	0.033	0.050	0.550*	0.408**	-								
7. Fear of missing out	0.150*	0.020	0.111	0.350**	0.415**	0.388**	-							
8. Self-control	0.021	-0.009	-0.019	-0.355**	-0.275**	-0.335**	-0.353**	-						
9. Mindfulness	-0.031	0.037	-0.123	-0.589**	-0.564**	-0.576**	-0.450**	0.488**	-					
10. Grit	0.022	0.067	-0.067	-0.360**	-0.222**	-0.331**	-0.301**	0.612**	0.429**	-				
11. BIS	0.022	0.036	0.083	0.286**	0.348**	0.261**	0.394**	-0.233**	-0.548**	-0.332**	-			
12. BAS-drive	0.049	0.010	-0.014	-0.161*	0.023	-0.078	0.100	-0.015	0.056	0.058	-0.059	-		
13. BAS-reward responsiveness	0.014	-0.007	-0.027	-0.074	-0.010	-0.014	0.248**	-0.132	-0.116	-0.099	0.465**	0.400**	-	
14. BAS-fun seeking	-0.067	0.014	-0.044	0.046	0.067	0.077	0.201**	-0.279**	-0.130	-0.275**	0.126	0.478**	0.454**	-
15. Smartphone addiction	-0.019	-0.050	0.124	0.261**	0.275**	0.278**	0.500**	-0.467**	-0.380**	-0.382**	0.207**	0.065	0.150*	0.161*

Note. * $p < 0.05$, ** $p < 0.001$.

Appendix 2

Table 4 Means and Standard Deviations of Standardized Scores of Indicators

	Self-controlled, gritty, & mindful ($n=45$)	Emotionally distressed ($n=63$)	Approach sensitive ($n=99$)	F
Depression	-0.83_a (0.42)	1.19_b (0.73)	-0.38_c (0.56)	190.4^{***}
Stress	-0.74_a (0.57)	0.96_b (0.94)	-0.28_c (0.69)	80.05^{***}
Loneliness	-0.84_a (0.72)	0.91_b (0.86)	-0.20_c (0.71)	75.52^{***}
Fear of Missing Out	-0.90_a (0.61)	0.65_b (1.04)	-0.01_c (0.77)	45.41^{***}
Self-control	1.07_a (0.79)	-0.53_b (0.82)	-0.15_c (0.81)	55.22^{***}
Mindfulness	1.22_a (0.56)	-0.88_b (0.73	0.003_c (0.66)	131.36^{***}
Grit	1.09_a (0.82)	-0.53_b (0.89)	-0.16_c (0.73)	57.07^{***}
BIS	-0.69_a (0.95)	0.51_b (0.93)	-0.01_c (0.88)	22.76^{***}
BAS-drive	-0.04_a (1.01)	-0.33_{ab} (0.99)	0.23_{ac} (0.94)	6.53^{**}
BAS-reward responsiveness	-0.38_a (1.01)	-0.23_{ab} (1.01)	0.32_c (1.06)	10.94^{***}
BAS-fun seeking	-0.52_a (0.89)	-0.05_b (1.04)	0.27_c (0.93)	10.73^{***}

Note. All values are standardized scores. Standard deviations are shown in parentheses. BIS = behavioral inhibition system; BAS = behavioral activation system. Mean scores sharing the same subscript in a row indicate that they are not significantly different from each other. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Authors' Contributions The authors confirm contributions to the paper as follows: study conception and design by H. Yang & S. Yang; data collection and analysis by H. Yang; interpretation of results by H. Yang, G. Tng, S. Khoo, & S. Yang; preparation of draft manuscript by all authors.

Funding This research was supported by a Lee Kong Chian fellowship and grant awarded to Hwajin Yang by Singapore Management University through a research grant (19-C242-SMU-008) from the Ministry of Education Academic Research Fund Tier 1 and a grant awarded to Sujin Yang by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2018S1A5A8027819).

Data Availability Data and materials will be available upon request.

Code Availability Code will be available upon request.

Declarations

Conflict of Interest The authors have no conflicts of interest to declare.

Ethics Approval Study procedures were approved by the university's institutional review board.

HEK, AMB, and LJT conceived and designed the experiment. HEK, AMB, and MJE collected and analyzed data. All authors contributed. to and approved the final manuscript.

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