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FULL-LENGTH REPORT

Bridging the links between Big Five personality traits and problematic smartphone use: A network analysis

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ABSTRACT

Background: Existing research has demonstrated that problematic smartphone use (PSU) may reflect a composition of heterogeneous symptoms, with individual PSU symptoms uniquely related to predisposing variables. The Big Five personality traits represent one of the most frequently examined predisposing variables in relation to PSU. However, no studies to date have examined the trait-to-symptom association between the Big Five personality traits and PSU. Using a network analysis approach, we aimed to understand: 1) specific pathways linking each of the Big Five personality traits to PSU symptoms and 2) the bridging effects of each Big Five personality trait on the PSU symptom cluster. *Methods:* A regularised graphical Gaussian model was estimated among 1,849 Chinese university students. PSU symptoms were assessed with items from the Problematic Smartphone Use Scale. Facets of the Big Five personality traits were assessed with the subscales of the Chinese Big Five Personality Inventory-15. An empirical index (i.e., bridge expected influence) was used to quantify bridge nodes. *Results:* Results revealed specific and distinct pathways between the Big Five personality traits and PSU symptoms (e.g., Neuroticism-Escapism/Avoidance, Conscientiousness-Preoccupation and Extraversion-Escapism/Avoidance). Further, Neuroticism showed the highest positive bridge centrality among the Big Five personality traits, while Conscientiousness had the highest negative bridge centrality. *Discussion and conclusions:* The current study provided direct empirical evidence concerning specific pathways between the Big Five personality traits and PSU symptoms and highlighted the influential role of Neuroticism and Conscientiousness as potential targets for early detection and treatment of PSU.

KEYWORDS

Big Five personality traits, network analysis, problematic smartphone use

INTRODUCTION

Problematic smartphone use (PSU) has been identified as an emerging public health problem, leading to significant health and societal costs (Rumpf, Effertz, & Montag, 2022; Sohn, Rees, Wildridge, Kalk, & Carter, 2019). PSU features uncontrolled/excessive use of smartphones that interfere with individuals' daily life functioning (Billieux, 2012). As symptoms of

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PSU resemble those found in substance use disorders and gambling disorders (e.g., preoccupation, loss of control and continuing despite problems), an addiction framework is often applied when characterising PSU (Brand et al., 2019; De-Sola Gutiérrez, Rodríguez de Fonseca, & Rubio, 2016; Yu & Sussman, 2020). For the current study, we adopted the addiction framework and defined PSU as an *addiction-like* pattern of smartphone use. Emerging research shows that PSU is prevalent among young adults, especially university students (Carbonell, Chamarro, Oberst, Rodrigo, & Prades, 2018; Csibi, Griffiths, Demetrovics, & Szabo, 2021). According to the latest research, the rate of PSU among Chinese university students was estimated to be 36.6% (Mei et al., 2022). Several studies demonstrated that PSU may be associated with psychological symptoms such as depression and anxiety (Elhai, Levine, & Hall, 2019; Mei et al., 2022), physical concerns such as musculoskeletal impairments (Regiani Bueno, Garcia, Marques Gomes Bertolini, & Rodrigues Lucena, 2019), as well as behavioural disturbances such as sleep impairments (Mei et al., 2022). Given the prevalence and potential negative consequences of PSU, it is important to identify its underlying mechanisms (Busch & McCarthy, 2021).

Personality traits have been identified as predisposing factors of PSU (Billieux, 2012; Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015; Brand et al., 2016, 2019). One influential PSU model, the Pathway Model, proposes that different personality traits may formulate distinct pathways toward PSU (Billieux, 2012; Billieux et al., 2015). The Big Five is one of the most widely used frameworks when conceptualising and empirically examining personality correlates of PSU. According to Costa and McCrae (1992), the Big Five personality traits define five facets of personality traits, namely, Neuroticism (the tendency to experience negative emotions), Extraversion (the tendency to be outgoing and seek social interactions), Openness (the tendency to be broadminded and seek new experiences), Agreeableness (the tendency to be tender-minded and concur with others), and Conscientiousness (the tendency to be self-disciplined and dependable). As the Big Five represents traits that exist before symptom onset, oftentimes, they are regarded as risk/protective factors for problematic/addictive behaviours (Kayiş et al., 2016).

The Pathway Model provides conceptual explanations about how certain facets of the Big Five may impact PSU. According to the Pathway Model, Neuroticism, Extraversion and Conscientiousness may drive risk for PSU through the excessive reassurance pathway, extraversion pathway and impulsive pathway, respectively. Specifically, individuals high in Neuroticism may be predisposed to PSU due to their need for reassurance from others or to alleviate negative emotions (Billieux, 2012; Billieux et al., 2015; Elhai, Dvorak, Levine, & Hall, 2017; Pivetta, Harkin, Billieux, Kanjo, & Kuss, 2019). Meanwhile, Extraversion may lead to PSU due to a strong desire for social interactions (i.e., extraversion pathway, Billieux, 2012; Billieux et al., 2015). Noteworthy, empirical evidence suggested that certain features of Extraversion (e.g., sensation seeking) may be more related to specific usage (i.e., dangerous smartphone use) rather than addiction-like symptoms per se (Dey et al., 2019). Lastly, individuals characterised by poor self-control and lack of planning (i.e., low conscientiousness) may be vulnerable to addictive smartphone use due to diminished impulse control (i.e., impulsive pathway; Gao et al., 2020).

Despite extensive research examining the relationships between the Big Five personality traits and PSU, mixed findings have been reported across the literature. Similar to other addictive behaviours (e.g., alcohol, nicotine, cannabis, and gambling disorder (Dash et al., 2019)), PSU is most consistently associated with high Neuroticism, low Agreeableness, and low Conscientiousness (Gao et al., 2020; Marengo et al., 2020). Meanwhile, findings on Extraversion and Openness in relation to PSU tend to be inconsistent (Gao et al., 2020; Marengo et al., 2020; Xiong, Xu, Zhang, Zhu, & Xie, 2021). For instance, the meta-analysis by Gao et al. (2020) reported a significant positive relationship between Extraversion and PSU, while other meta-analytic studies reported non-significant results (Marengo et al., 2020; Xiong et al., 2021). Additionally, Openness showed negative associations with PSU in Marengo et al. (2020), but no such relationship was found in Gao et al. (2020). These inconsistencies call for further clarification on the relationships between the Big Five personality traits and PSU.

Existing studies often characterise PSU as a unitary construct (indexed by the symptom sum score; e.g., Hussain, Griffiths, & Sheffield, 2017; Takao, 2014) when estimating the relationship between the Big Five personality traits and PSU. In the context of PSU, such assumptions may be especially problematic as it diminishes the potential heterogeneity of PSU symptoms. Emerging research argues that PSU may be better conceptualised as a constellation of heterogeneous symptoms, which differ from one another in important dimensions (Andrade et al., 2020; Gao, Zhao, Chu, Chen, & Li, 2022; Huang, Lai, Li, Luo, & Wang, 2021). For instance, recent studies found that individual PSU symptoms are uniquely related to vulnerability factors, including fear of missing out (Huang et al., 2021), behavioural inhibition/activation systems (Gao et al., 2022) and intolerance of uncertainty (Liu, Ren, et al., 2022). Neglecting the symptomatic heterogeneity of PSU may mask the differential relationships between distinct symptoms and personality traits, potentially contributing to inconsistent findings across studies. A symptom-based approach may facilitate a more consistent understanding of the trait-to-symptom relationships between the Big Five personality traits and PSU.

The present study utilised a promising symptom-based approach, namely, network analysis, to examine relations between the Big Five traits and PSU. From a network perspective, psychopathology can be viewed as a network of variables (nodes) and causal pathways (edges) between them (Epskamp, Borsboom, & Fried, 2018; McNally, 2016). In a combined network model with the Big Five traits and PSU symptoms, nodes may reinforce/inhibit each other to different degrees, depending on the strength of their direct

associations (edge weights). In this way, network analysis moves beyond examining how the Big Five personality traits may correlate to the PSU construct (indexed by the symptom score) to analysing the direct trait-to-symptom relationships.

There are two methodological advantages that make network analysis distinguishable from traditional statistical models. First, network analysis helps visualise the direct associations between individual symptoms and their predisposing variables in an insightful way (Bringmann & Eronen, 2018). By inspecting the network structure, researchers may get a direct understanding of which PSU symptoms are most closely related to each of the Big Five personality traits and pathways linking the Big Five personality traits to PSU symptoms. Second, network analysis offers novel indices to analyse how relevant predisposing variables may affect symptom clusters (Fried & Cramer, 2017). Specifically, the bridge expected influence could quantify to what extent each Big Five personality trait may activate/deactivate (transmit positive/negative effects) the PSU symptom cluster (Jones, Ma, & McNally, 2021). Such information may be critical when selecting potential targets for therapeutic activation and deactivation (Robinaugh, Millner, & McNally, 2016).

The current study used network analysis to explore the symptom-level relationships between the Big Five traits and PSU. By examining the network structure and bridge centrality index, we aimed to understand: 1) the specific pathways (edges) linking each of the Big Five personality traits to PSU, and 2) the bridging effects of each Big Five personality trait on the PSU symptom cluster. Based on the meta-analytic reviews conducted on this topic (Gao et al., 2020; Marengo et al., 2020), we hypothesised that: i) Neuroticism would activate the PSU symptom cluster, and ii) Agreeableness and Conscientiousness would deactivate the PSU symptom cluster. Given the novelty of the symptom-level analysis, no specific hypotheses were generated regarding symptom pathways.

METHOD

Participants

We conducted a survey through a Chinese online survey platform (Wenjuanxing). Participants were recruited from five universities in Shaanxi Province, China. Informed consent was obtained from all participants prior to participation. Demographic information was collected at the start of the survey. All questions in the survey were set as forced responses (i.e., participants need to provide responses to all questions before they can submit). Therefore, there were no incomplete responses. One hundred and seventy-six participants were excluded due to failing the two attention check items (e.g., participants did not choose the second option when they responded to "Please choose the second option for this question") or demographic items (e.g., participants filled in "100 years old" when they responded to the "Age" question, while it was later confirmed that there were no students of such age among the respondents). The sample consisted of 1849 participants (59.2% female, Mean age = 19.0, SD = 1.3, Range = 17–23 years).

Measures

Problematic Smartphone Use Scale (PSUS; Richardson, Hussain, & Griffiths, 2018): The Chinese translated nine-item PSUS was used to measure PSU over a 12-month period (Richardson et al., 2018). At the time when the study was designed and conducted, this was the only scale that adopted the Diagnostic and Statistical Manual of Mental Disorders (fifth edition) criteria for Internet Gaming Disorder and comprehensively addressed nine symptoms (i.e., Preoccupation, Withdrawal, Tolerance, Loss of control, Giving up other activities, Continuing despite problems, Deception, Escapism/Avoidance, and Negative consequences) characterise addictive behaviours. The measured symptoms also reflect diagnostic criteria for substance use disorders and gambling disorders (Petry et al., 2014), which may facilitate testing transdiagnostic concepts in addiction research, a research priority proposed by experts in the addiction field (Yücel et al., 2019).

The PSUS (with "gaming" replaced by "smartphone use") has been used to measure PSU in several existing studies, with good internal consistency (Cronbach' α ranged from 0.85 to 0.86; Hussain et al., 2017; Mitchell & Hussain, 2018; Richardson et al., 2018). Additionally, the scale sum score showed positive correlations with smartphone usage time across studies (Hussain et al., 2017; Mitchell & Hussain, 2018; Richardson et al., 2018). Sample items include "Have you lost interest in previous hobbies and other entertainment activities as a result of your engagement with the smartphone?" and "Have you jeopardised or lost an important relationship, job or an educational or career opportunity because of your smartphone use?". Participants were asked to report on a 5-point Likert-type scale, ranging from 1 ("never") to 5 ("very often"). The scale demonstrated good internal consistency in the current study (Cronbach's alpha = 0.89).

The Chinese Big Five Personality Inventory-15 (CBF-PI-15; Zhang, Wang, He, Jie, & Deng, 2019): The Chinese Big Five Personality Inventory-15 was used to measure five facets of the Big Five personality traits. Each subscale consisted of three items, measuring Neuroticism, Conscientiousness, Agreeableness, Openness and Extraversion. Participants were asked to report on a six-point Likert-type scale, ranging from 1 ("disagree strongly") to 6 ("agree strongly"). Sample items include "I often feel disturbed (Neuroticism)", "One of my characteristics is doing things logically and orderly (Conscientiousness)", "I think most people are well-intentioned (Agreeableness)", "I'm a person who loves to take risks and break the rules (Openness)" and "I like to go to social and recreational parties (Extraversion)". The internal consistency of each subscale (i.e., Neuroticism, Conscientiousness, Agreeableness, Openness and Extraversion) is 0.82, 0.68, 0.72, 0.83 and 0.80, respectively.

Analysis

An Extended Bayesian Information criterion (EBIC) graphical least absolute shrinkage and selection operator (LASSO) network model was estimated (Epskamp & Fried, 2018). Within the estimated network, variables of interest are depicted as nodes. We predefined two clusters of nodes, namely, the personality cluster (subscale scores of the Chinese Big Five Personality Inventory-15) and the symptom cluster (item score of the PSU scale). Edges represent partial (Spearman) correlations between nodes, after controlling for all remaining nodes within the network (Epskamp et al., 2018).

The LASSO regularisation algorithm shrank small correlation coefficients to zero, so that only the most robust edges were retained. This procedure helped to produce a sparser and more interpretable network (Costantini et al., 2015; Epskamp & Fried, 2018). Following the recommendations by Epskamp and Fried (2018), the tuning parameter was set as 0.5 to balance sensitivity and specificity. Force-directed Fruchterman–Reingold algorithm was utilised for the network visualisation (Fruchterman & Reingold, 1991). Closely connected nodes were placed next to each other while unconnected nodes were placed farther apart. The valence of the between-nodes correlation was depicted as the colour of edges (blue–positive; red–negative). The magnitudes of between-nodes correlation (i.e., edge weight) was represented by edge thickness. Network construction and visualisation was computed via the *qgraph* package (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012) in R.

We calculated bridge expected influence (i.e., the sum of connectivity between a given node and all nodes of the other cluster (Jones et al., 2021); to identify influential nodes that may share inter-cluster connections. Bridge expected influence is an appropriate centrality index to use when there are both positive and negative edges within the network. The raw scores of bridge expected influence were depicted. The trait with a high positive bridge expected influence indicates that it was positively related to various PSU symptoms, and hence may be considered as the risk factor of PSU. Meanwhile, the trait with a high negative bridge expected influence may be identified as the protective factor of PSU. The R package *networktools* was used to compute the bridge expected influence value of each node within the network (Jones, 2018).

The following procedures were taken to ensure the accuracy and stability of the presented network. Firstly, we bootstrapped (with 2,000 bootstrapped samples) the non-parametric Confidence Intervals (CIs) of each edge within the network. Narrow bootstrapped CIs indicate that the estimated network was accurate. Secondly, we conducted a case-dropping bootstrap procedure (with 2,000 bootstrapped samples) to calculate the correlation stability (CS)-coefficient for bridge expected influence. The optimal cut-off for (CS)-coefficient is 0.5 (Epskamp et al., 2018). Thirdly, we performed bootstrapped difference tests for edge weights and bridge expected influences to examine whether two edge weights or two node bridge expected influences differed significantly from one another. The three procedures were conducted using the *bootnet* package (Epskamp & Fried, 2020).

Ethics

Informed consent was obtained from all participants. All procedures in this study were in accordance with the Declaration of Helsinki and the study protocol was approved by the Ethics Committee of the First Affiliated Hospital of the Fourth Military Medical University (Project No.KY20202063-F-2).

RESULTS

Majority of participants were in their first year of university (70.3%). Table 1 displays descriptive statistics of all measured variables.

The estimated network is presented in Fig. 1a. Out of 45 possible between-cluster edges, 23 edges (51%) have non-zero edge weights (weight ranged from −0.10 to 0.22) and are kept in the network. Neuroticism was positively correlated with 7 (out of 9; weight ranged from 0.01 to 0.22) PSU symptoms. The strongest edge was between neuroticism and PSU 8 (Escapism/Avoidance; edge weight = 0.22). Conscientiousness was negatively correlated with 7 (out of 9; weight ranged from −0.09 to −0.02) PSU symptoms and had a strong negative connection to PSU 1 (Preoccupation; edge weight = −0.09). Agreeableness was negatively correlated with 3 (out of 9; weight ranged from −0.04 to −0.004) PSU symptoms. A strong negative edge was between Agreeableness and PSU 9 (Negative consequences; edge weight = −0.04). Openness was negatively correlated with 3 (out of 9; weight ranged from −0.02 to −0.015) PSU symptoms and had a notable negative association with PSU 1 (Preoccupation; edge weight = −0.02). Extraversion was negatively correlated with 3 (out of 9; weight ranged from −0.10 to −0.04) PSU symptoms. A strong negative association was observed between Extroversion and PSU 8 (Escapism/Avoidance; edge weight = −0.10). The bootstrapped 95% confidence interval is relatively narrow, indicating that the edges of the IU-PSU network are accurate (Figure S1 in Supplementary Material). Figure S2 (in Supplementary Material) shows the bootstrapped difference test for edge weights.

The raw bridge expected influence values are depicted in Fig. 1b. Among all nodes, Neuroticism exhibits the highest positive bridge expected influence, while Conscientiousness exhibits the highest negative bridge expected influence. The CS-coefficient for bridge expected influence (value = 0.75) was larger than 0.50, indicating the bridge expected influence values are highly stable (Figure S3 in Supplementary Material). The bootstrapped difference test showed that Neuroticism (positive value) and Conscientiousness (negative value) were significantly different from other facets of the Big Five personality traits in terms of bridge expected influence estimates (Figure S4 in Supplementary Material).

DISCUSSION

The current study represents the first attempt to examine the interrelationships between the Big Five personality

Table 1. Mean scores and standard deviations for each variable selected in the present network

Variables	M (SD)/N (%)
Year level	
First year	1,299 (70.3)
Second year	287 (15.5)
Third year	168 (9.1)
Fourth year	40 (2.2)
Fifth year	55 (3.0)
Neuroticism	8.7 (3.4)
Conscientiousness	12.4 (2.6)
Agreeableness	13.4 (2.9)
Extraversion	10.9 (3.2)
Openness	11.0 (3.5)
PSU 1 ("Do you feel preoccupied with your smartphone use? (Some examples: Do you think about previous smartphone use or anticipate the next smartphone use? Do you think smartphone use has become the dominant activity in your daily life?"; Preoccupation)	2.7 (1.0)
PSU 2 ("Do you feel more irritability, anxiety or even sadness when you try to either reduce or stop your smartphone use?"; Withdrawal)	1.6 (0.8)
PSU 3 ("Do you feel the need to spend increasing amounts of time engaged in smartphone use in order to achieve satisfaction or pleasure?"; Tolerance)	1.8 (0.9)
PSU 4 ("Do you systematically fail when trying to control or cease your smartphone use?"; Loss of control)	2.2 (1.0)
PSU 5 ("Have you lost interest in previous hobbies and other entertainment activities as a result of your engagement with the smartphone?"; Giving up other activities)	1.6 (0.8)
PSU 6 ("Have you continued your smartphone use despite knowing it was causing problems between you and other people?"; Continuing despite problems)	1.8 (1.0)
PSU 7 ("Have you deceived any of your family members, therapists or others because of the amount of your smartphone use?"; Deception)	1.7 (0.8)
PSU 8 ("Do you use your smartphone in order to temporarily escape or relieve a negative mood (e.g., helplessness, guilt, anxiety)?"; Escapism/Avoidance)	2.2 (1.1)
PSU 9 ("Have you jeopardised or lost an important relationship, job or an educational or career opportunity because of your smartphone use?"; Negative consequences)	1.5 (0.8)
PSU total	17.0 (6.1)

Abbreviations: M, Mean; SD, standard deviation

traits and PSU using a symptom-based network approach. The symptom-level analysis adds to previous findings by pinpointing distinct symptom pathways between the Big Five personality traits and PSU. In regard to our first aim, we found several distinct pathways (both positive and negative) between the Big Five personality traits and PSU symptoms (e.g., Neuroticism-Escapism/Avoidance, Conscientiousness-Preoccupation and Extraversion-Escapism/Avoidance), with the strongest positive pathway emerging between Neuroticism and Escapism/Avoidance. The bridge centrality analysis supported our second aim and research hypotheses. Specifically, we found that Neuroticism activates the PSU symptom cluster while Agreeableness and Conscientiousness deactivate the PSU symptom cluster. In addition, we showed that Extraversion and Openness may deactivate the PSU symptom cluster.

By pinpointing specific pathways that link the Big Five personality traits to PSU, our results support prior theoretical assumptions on mechanisms underlying PSU. Specifically, it has been proposed that the excessive reassurance pathway linking Neuroticism and PSU is relevant to negative reinforcement i.e., individuals engage in smartphone use as a coping strategy to address negative emotions (Elhai et al., 2017; Pivetta et al., 2019), a well-documented mechanism underlying addictive behaviours (Baker, Piper, McCarthy, Majeskie, & Fiore, 2004; Liu et al., 2021; Liu, Rotaru, Chamberlain, Ren, et al., 2022; Liu, Rotaru, Chamberlain, Yücel, et al., 2022). In line with this view, numerous studies reported positive associations between Neuroticism and overall PSU (Gao et al., 2020; Marengo et al., 2020). By showing the edge between Neuroticism and Escapism/Avoidance, we highlighted the specific symptom that might drive the Neuroticism-PSU association. This extends previous findings at the PSU construct level by providing more direct support of the negative reinforcement hypothesis. Similarly, the negative edges between Conscientiousness and symptoms characterised by Loss of Control and Preoccupation directly supported the impulsive pathway, which proposes that impulse control and regulation may explain the inverse association between Conscientiousness and PSU (Gao et al., 2020).

Interestingly, we found that Extraversion and Openness negatively mapped onto the same PSU symptoms (i.e., Preoccupation, Giving up other activities and Escape/Avoidance). The similar (inverse) edges may be explained by emotionality (i.e., the ability to perceive, express, and connect with emotions in self and others and maintaining successful interpersonal relationships; Feher, Yan, Saklofske, Plouffe, & Gao, 2019). Both Extraversion and Openness have been positively associated with emotionality (Petrides et al., 2010). The successful interpersonal relationships in real life may make individuals less likely to engage in excessive socially-motivated smartphone use as a compensation strategy (Kardefelt-Winther, 2014). Further, the ability to perceive, express, and connect with emotions may reduce the likelihood of using smartphones to regulate negative emotions.

Despite being consistently reported as a protective factor for PSU, the role of Agreeableness was not highlighted in PSU models (Billieux, 2012; Billieux et al., 2015; Brand et al., 2016, 2019). Our results showed a negative edge between Agreeableness and Negative consequences, indicating that perceptions and sensitivity over conflict may underpin the protective effect of Agreeableness (Jensen-Campbell & Graziano, 2001).

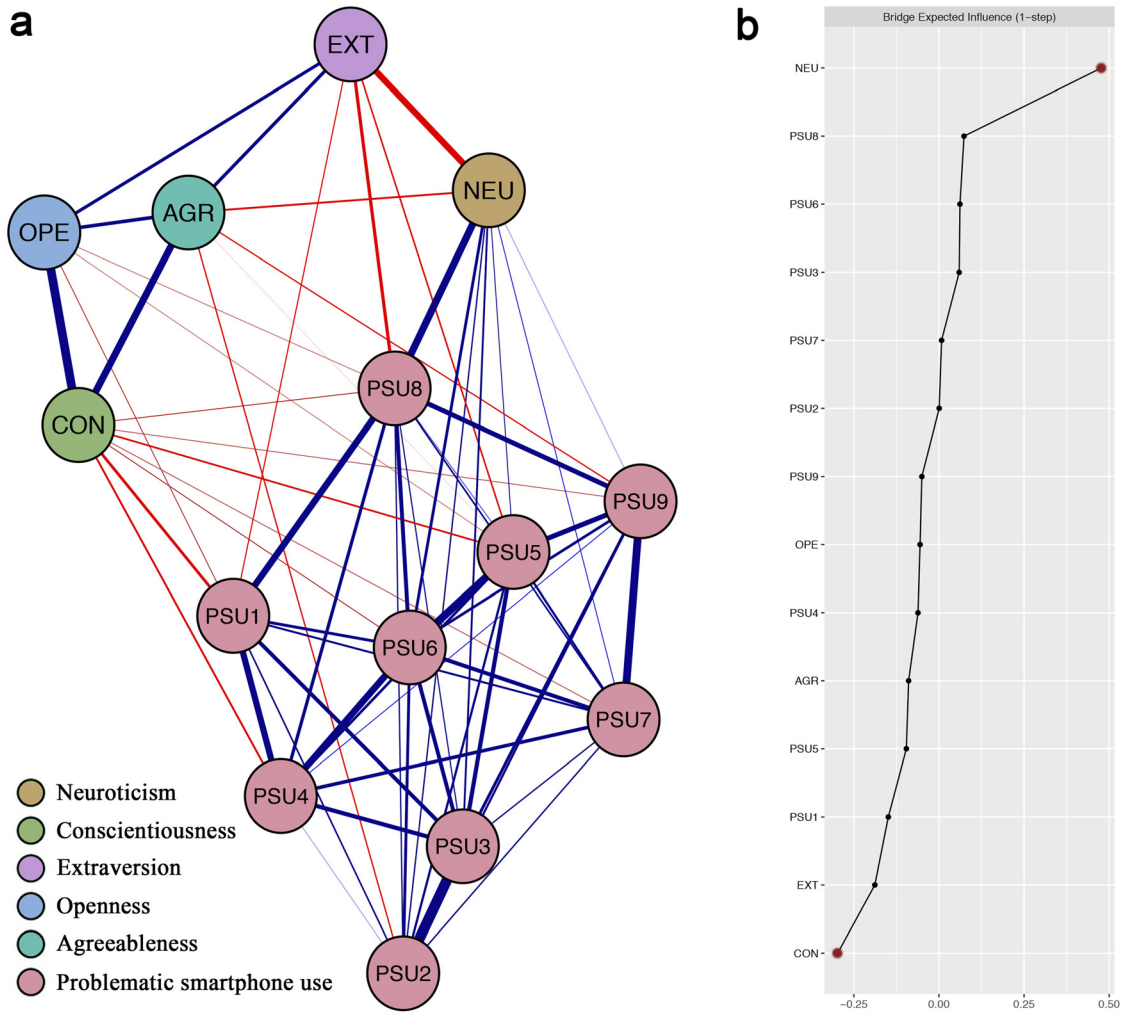

Fig. 1. (a) Network structure of different facets of the Big Five personality traits and PSU symptoms. Blue edges represent positive partial correlations, red edges represent negative partial correlations. The thickness of the edge reflects the magnitude of the correlation. Cut value = 0.03. A full description of PSU items is reported in Table 1. (b) Bridge centrality plot. Red dots denote the bridge nodes

Specifically, individuals high on Agreeableness may be more sensitive to detect intra- and interpersonal conflicts (e.g., identifying early signs of conflicts). Hence, they are more likely to change their behaviours before/as soon as the Negative consequences occur. This initial finding should be further tested as it may ultimately expand current theoretical frameworks (e.g., the Pathway Model) on PSU.

Findings from bridge centrality analysis are partially in line with previous meta-analyses, with Neuroticism activating the PSU symptom cluster and Agreeableness and Conscientiousness deactivating the PSU symptom cluster (Gao et al., 2020; Marengo et al., 2020). Meanwhile, Extraversion and Openness were negatively bridged onto the PSU symptom cluster. The findings on Neuroticism (with the highest positive bridge expected influence) and Conscientiousness (with the highest negative bridge expected influence) may have important implications when developing interventions for PSU. It has been suggested that bridge nodes may represent the most crucial intervention targets, as addressing such nodes may result in changes in the co-occurring symptom cluster (Jones et al., 2021). Based on our findings, reducing Neuroticism (the node that transmits the highest positive effect to the PSU symptom cluster) and improving Conscientiousness (the node that transmits the highest negative effect to the PSU symptom cluster) may be effective when addressing PSU.

It has been highlighted that clarifying the possible role of personality features, promoting early identification of at-risk individuals and generating effective interventions should be prioritised for future research (Fineberg et al., 2018). In response to the first recommendation, we delineated specific pathways among the Big Five personality traits and PSU symptoms, which provides a more nuanced understanding of how individual differences may drive specific PSU symptoms. Regarding early identification, our findings suggest that the three-item Neuroticism subscale may be used to identify individuals at increased risk of PSU in a time-efficient manner. Lastly, the symptom pathways and two bridge nodes we identified may provide empirical evidence for intervention developments. For instance, training coping skills may be particularly relevant to individuals with high Neuroticism levels as this may reduce their overreliance on

avoidance coping, such as smartphone use. Given the potential transdiagnostic mechanisms (negative reinforcement) discussed above, such personalised interventions may even be promising in improving various addictive behaviours. Meanwhile, the digital personality change intervention has demonstrated significant and persisting effects in decreasing Neuroticism levels and increasing Conscientiousness levels (Stieger et al., 2021). Thus, it may be considered a candidate intervention for PSU.

Limitations

Despite important inputs from current findings, several limitations should be noted when interpreting the results. First, the assumptions behind the theoretical framework for this study is that personality traits may formulate pathways that predict PSU (rather than the other way around, as proposed in (Billieux, 2012; Billieux et al., 2015), and results were discussed accordingly. Yet, as the current study adopted a cross-sectional design, we may not rule out the possibility that the Big Five personality traits are influenced by PSU symptoms (e.g., engaging in smartphone use to downregulate negative feelings may exacerbate pre-existing Neuroticism).

Second, the study utilised a convenience sample of Chinese university students, which may limit its generalizability to other populations. Yet, a recent meta-analysis suggested China has the highest rates of PSU among 24 examined countries (Olson et al., 2022). Thus, understanding the underlying mechanism of PSU in this high-risk population is important. Third, PSU was measured using self-report scales, which may induce self-report biases. Future research may consider using more objective PSU data, i.e. server log data to build a direct measure of participants' smartphone use patterns, although such approach is subject to technical and ethical concerns and therefore should be considered with caution. Fourth, the PSUS is a relatively new PSU measure, which may restrict the comparability of the results available in the literature.

CONCLUSION

The current study contributes to the existing literature on the Big Five personality traits and PSU. By adopting a symptom-based network approach, the study is the first to reveal specific pathways that link the Big Five personality traits to PSU symptoms, shedding light on unique protective and vulnerability mechanisms. We further identified the influential role of Neuroticism and Conscientiousness in relation to PSU, which may have potentials to inform early identification and preventative interventions for PSU.

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Authors' contribution: C.L., R.L, and L.A. developed study idea and design. C.L wrote the original draft of this manuscript. All authors contributed to revising subsequent versions of the paper.

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SUPPLEMENTARY MATERIALS

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