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The Longitudinal Comorbidity of Specific Problematic Internet Use and Psychological Distress: A Cross-Lagged Panel Network Analysis

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Abstract

Studies have used network analysis to show the progression of problematic internet use (PIU). The present study examined the longitudinal comorbidity network models of specific types of PIU and psychological distress over time. A total of 685 undergraduate students (mean age = 19.12 years) completed three waves of surveys assessing two specific types of PIU (problematic social media use [PSMU] and problematic online video watching [POVW]) and psychological distress (depression, anxiety, and stress). Results showed that the 'down-heartedness' symptom of depression and the 'agitation' symptom of stress were consistently the most central symptoms in the PIU-psychological distress comorbidity network. 'Mood modification' and 'conflict/functional impairment' related to social media were the bridging symptoms that connected the other symptoms in the first two waves of studies. The 'no initiative' symptom of depression became the key bridging symptom in the third wave. Similarly, cross-lagged panel network analysis showed that PSMU symptoms (e.g., 'conflict/functional impairment') were the most influential and susceptible symptoms in earlier waves, while depression symptoms became key predictors of other symptoms over time in the comorbidity network. The findings provide new perspectives and means for the diagnosis and treatment of PIU and associated mental health illnesses.

Keywords: problematic internet use; problematic social media use; problematic online video watching; psychological distress; longitudinal comorbidity; cross-lagged panel network analysis

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Introduction

The internet has become an integral part of people's lives, and studies have investigated the negative effects of excessive, problematic, or addictive internet use since the mid-1990s (Griffiths, 1996; Young, 1998). Problematic internet use (PIU), sometimes used interchangeably with terms such as 'internet addiction' (IA), has been widely used as an umbrella concept to describe different types of uncontrolled internet use that results in psychological dependence, addictive symptoms, and significant functional impairments (Baggio et al., 2022; Liu & Potenza, 2007; Shapira et al., 2000). The association between PIU and psychological distress has been explored and confirmed in

many studies (e.g., Hussain et al., 2020; Lopes et al., 2022; Marttila et al., 2021; Ostovar et al., 2016; Teng et al., 2021; Twigg et al., 2020; W. Zhou et al., 2023). Identifying the specific central symptoms in the association between PIU and psychological distress is important for the development of possible interventions (Bai et al., 2022; Zhao et al., 2023).

Recent studies have used network analysis to investigate the comorbidity networks of PIU and psychological distress, as well as the dynamic characteristics of connections between associated variables or symptoms (Cai et al., 2021; Jia et al., 2024; Qu et al., 2024; Wang et al., 2022; Zhao et al., 2023). However, network analysis studies have mainly examined generalized PIU using cross-sectional designs. Longitudinal network analysis focusing the development of the relationship between specific types of PIU and psychological distress are scarce. Different types of specific PIU might involve distinct behavioral patterns and psychological mechanisms (Baggio et al., 2022; Starcevic & Aboujaoude, 2017). For example, individuals may exhibit greater difficulties with attentional inhibitory control when bingewatching TV series and online pornography compared to playing videogames (Cervigón-Carrasco et al., 2023). Because cross-sectional studies are limited in capturing the temporal dynamics and reciprocal relationships between specific PIU and psychological distress symptoms, longitudinal network analysis is optimal for identifying central symptoms that may perpetuate maladaptive cycles and inform targeted intervention efforts. Therefore, it is necessary to explore the connections between specific PIU and psychological distress symptoms over time using a longitudinal network analysis approach.

Problematic Internet Use and Psychological Distress

Studies have often conceptualized uncontrolled internet use that leads to negative consequences as an addiction (Brand et al., 2014, 2019; Griffiths, 2005; Young, 1998; Zhao et al., 2023). It has been posited that addictive internet use, similar to other behavioral addictions (e.g., gambling addiction, gaming addiction, exercise addiction, work addiction, smartphone addiction, etc.), comprise six components: salience, mood modification, tolerance, withdrawal, conflict and relapse (Griffiths, 2005). However, IA or PIU was not included in the fifth edition (text revision) of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5 TR; American Psychiatric Association, 2022) or the 11th revision of the International Classification of Diseases ICD-11 (World Health Organization, 2019). The only two behavioral addictions that are included in the DSM-5 and ICD-11 are gambling disorder and (internet) gaming disorder.

It is also necessary to avoid overpathologizing passionate entertainment behaviors as addiction (Billieux et al., 2015). Therefore, several studies have used the term 'problematic internet use' rather than 'internet addiction' to describe excessive online behaviors that negatively affect daily life but do not reach the severity of addiction (I.-H. Chen et al., 2021; Kuss & Lopez-Fernandez, 2016). The present study uses the term 'PIU' which is defined as excessive internet use that leads to functional impairment (Billieux et al., 2017).

Various theories have indicated the association between PIU and psychological distress (Brand et al., 2019; Davis, 2001; Sonuga-Barke et al., 2024). The cognitive-behavioral model of pathological internet use (Davis, 2001) suggests that mental health issues such as depression can predict pathological internet use. The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors posits that the development of addictive behaviors is a dynamic process with distinct early and late mechanisms, including cue reactivity and decision-making initially, and habitual actions and automated responses later. Addictive behaviors are the consequence of the interaction between personal characteristics (e.g., psychopathology variables) and responses to cues or triggers. Specific addictive behaviors may play a role in the stabilization and intensification of predisposing variables (Brand et al., 2019). Similarly, a recent theoretical framework ('reciprocal pathways between digital activity and depressed mood') proposes that there are reciprocal pathways between digital activities and depression. Engaging in risky online behaviors can potentially lead to depressive moods by consistently triggering negative emotions and thoughts, such as anger and self-criticism. (Sonuga-Barke et al., 2024). Empirical evidence has shown that poor mental health conditions can predict higher PIU (e.g., Tian et al., 2024; Zhang & Bian, 2021), and PIU may in turn lead to greater psychological distress (e.g., M. Zhou et al., 2022).

Starcevic and Aboujaoude (2017) argue that it is important to focus on specific activities rather than the general concept of IA. Since Davis (2001) emphasized the importance of differentiating between generalized and specific pathological internet use, an increasing number of studies have confirmed the associations between specific forms of PIU, such as problematic social media use (PSMU) and problematic online video watching (POVW), and psychological distress. (e.g., anxiety, depression, stress; Hussain et al., 2020; Kircaburun et al., 2021; Lopes et al., 2022; Ostovar et al., 2016; Yan et al., 2023). Longitudinal studies also demonstrated the bi-directional link between

specific types of PIU (e.g., PSMU) and psychological distress and poor well-being (I.-H. Chen et al., 2021; J.-B. Li et al., 2018; Marttila et al., 2021; Teng et al., 2021; Twigg et al., 2020; W. Zhou et al., 2023). Based on the aforementioned definition of PIU, PSMU and POVW can be defined as the specific activities of using social media and watching online videos that lead to functional impairment and other negative consequences in individuals' daily lives including the compromising of interpersonal relationships, education and/or occupation (Billieux et al., 2017; Brand et al., 2019).

Overall, the positive association between specific PIU and psychological distress has been confirmed by both theoretical models and robust empirical studies. However, most studies have analyzed the relationship between the total scores on scales assessing PIU and psychological distress and have paid limited attention to the specific symptoms or measurement items of PIU or psychological distress. Further exploration of the link between PIU and psychological distress from a symptom-focused perspective is necessary. For instance, it remains unknown how features of addictive behaviors (e.g., withdrawal and tolerance, initially proposed in the components model of addiction) are connected with symptoms of anxiety, depression, or stress. It is therefore imperative to investigate the influence of these components on the relationship between specific PIU manifestations and mental health. Understanding which symptoms are central in the relationship between PIU and psychological distress is also essential for the implementation of potential interventions.

Network Analysis Studies of Problematic Internet Use

In recent years, the emerging approach of network analysis has been increasingly employed by scholars to examine the intricate structure of PIU and its complex interplay with psychological variables (Y. Yang et al., 2022, 2023; Zhao et al., 2023; see Table 1). Through the construction of network models, researchers can pinpoint the central symptoms of PIU in longitudinal studies (Belvederi et al., 2020; Epskamp et al., 2017; Qu et al., 2024). A central symptom is defined as a node exhibiting either the highest number of strong connections to other nodes in the network, or the highest centrality indices (e.g., strength, betweenness, or closeness centrality) within the network analysis framework (Epskamp et al., 2018).

In a network analysis study of PIU, Bai et al. (2022) identified 'preoccupation with the internet' and 'impaired functioning' as the central symptoms of PIU among patients with major depressive disorder. Cai et al. (2021) reported that factors such as 'academic decline due to internet use', 'depressed/moody/nervous only while being offline', and 'others complain about your time spent online' were the central symptoms in the PIU-anxiety network. However, this study focused solely on anxiety as a mental health issue, while other variables such as depression and stress were not included in the comparison. In addition, a study of PIU among adolescents with autism spectrum disorders identified 'defensive and secretive behaviors' and 'concealment of internet use' as the central symptoms of PIU (Hirota et al., 2021). Among 2,845 non-clinical adolescents and young adults, 'fear about boredom if offline' and 'uncontrollable use' were highlighted as key factors triggering and exacerbating other symptoms of PIU, while 'affected study and work' were the outcome symptoms (Lu et al., 2022).

Network analysis has emerged as a valuable analytical method in research examining specific forms of PIU. For instance, some studies have found that PSMU may be associated with specific depressive symptoms, with central symptoms such as 'fatigue,' 'loneliness,' and 'lack of enthusiasm' being reported (Aalbers et al., 2019; Wang et al., 2022). Wang et al. (2022) found that 'lack of enthusiasm', as a symptom of depression, was the most central symptom in the comorbidity network of PSMU, anxiety, and depression. 'Conflict/functional impairment' in PSMU had the highest betweenness value. This indicates the higher significance of depression symptoms compared to anxiety symptoms within the PSMU-anxiety-depression network. Betweenness centrality is a metric that quantifies a node's 'bridging role' in a network, reflecting how frequently the node lies on the shortest paths between other node pairs. Another cross-sectional network analysis study conducted among a large sample in China found that conflict and mood modification were the key bridging nodes in the network connecting PSMU with mental health risk symptoms (Peng & Liao, 2023). A different network analysis indicated that problematic online behaviors manifest as distinct entities or communities rather than in a single category of internet or smartphone addiction, which again emphasizes the need to focus on specific forms of PIU (Baggio et al., 2022).

Table 1. *Summary of Previous Network Analysis Studies Examining PIU and Psychological Distress.*

Study	Variables	Central nodes	Network analysis approach
Bai et al. (2022)	IA; quality of life	Preoccupation with the internet; Job performance or productivity suffer because of the internet; Neglect chores to spend more time online	Cross-sectional
Cai et al. (2021)	IA; anxiety	Academic decline due to internet use; Depressed/moody/nervous only while being off-line; School grades suffer due to internet use; Others complain about your time spent online	Cross-sectional
S. Chen & Zhu, (2023)	IGD; gaming motivations	Sense of victory; Enjoy being in the gaming world; Sense of achievement	Longitudinal
Hirota et al. (2021)	IA	Academic efficiency declines due to internet use; Life boring and empty without the internet; Anticipation for future online activities; Prefer the excitement online to the time with others	Cross-sectional
Jia et al. (2024)	PIU; depression	Interpersonal and physical problems; Tolerance symptoms; Loss of energy; Withdrawal symptoms; Time management problems	Longitudinal
L. Li et al. (2021)	Gaming disorder; depression; alexithymia; boredom; loneliness	Loneliness; Boredom	Cross-sectional
Y. Li et al. (2023)	IGD; PSU; PSMU; depression; anxiety; stress; meaning in life	Withdrawal; Mood modification; Tolerance	Cross-sectional
Lu et al. (2022)	IA	School work suffers; Job performance suffers; Fear about boredom if offline; Fail to stop being on the web; Fantasize about being on the web; Defensive or secretive about being on the web; Hidden web time	Cross-sectional
Marttila et al. (2021)	PSMU; loneliness; life satisfaction	PSMU; Loneliness; Life satisfaction	Cross-sectional; Longitudinal
Peng & Liao (2023)	PSMU; depression; anxiety; stress	Conflict; Mood modification	Cross-sectional
Qu et al. (2024)	Short video addiction; depression	Tolerance; Anhedonia; Conflict; Sad mood; Salience; Sleep	Longitudinal
Sánchez-Fernández et al. (2024)	generalized PIU; PSMU; problematic online gaming; Depression, Anxiety, and Stress; emotional role	Coping or mood modification; Withdrawal; Preoccupation; Relapse; Continuation despite problems; Depression; Anxiety; Stress	Cross-sectional
Tullett-Prado et al. (2023)	social media addiction; depression; anxiety; stress	Tolerance; Mood modification	Longitudinal
Wang et al. (2022)	PSMU; anxiety; depression	Salience; Conflict; Enthusiasm	Cross-sectional
Y. Yang et al. (2022)	IA; quality of life	Request an extension for longer time spent online; Preoccupation with the internet; Failure to cut down the time spent online	Cross-sectional
Y. Yang et al. (2023)	IA; suicidality	Request an extension for longer time spent online; Depressed/moody/nervous only while being offline; Sleep loss due to late night logins	Cross-sectional
Zhao et al. (2023)	IA; depression	Escape; Irritable; Energy; Guilty	Longitudinal

Note. IA: internet addiction; IGD: internet gaming disorder; PIU: problematic internet use; PSU: problematic smartphone use; PSMU: problematic social media use.

Guo et al. (2022) reported that the PSMU symptoms 'mood modification' and 'relapse' were closely connected with 'motor impulsivity' in the network community of impulsivity symptoms. Network analysis studies have shown that among adolescent and college student populations, problematic online behaviors (e.g., online gaming disorder and PSMU) were associated with psychological distress variables or symptoms such as loneliness, depression, alexithymia, and stress (L. Li et al., 2021; Y. Li et al., 2023; Sánchez-Fernández et al., 2024).

Longitudinal Network Analysis Studies

Longitudinal network analysis provides a nuanced perspective over general network analysis by capturing the evolution of network dynamics, thereby enhancing the precision of predictions about future state and behaviors within the network (S. Chen & Zhu, 2023; Tullett-Prado et al., 2023). Recognizing the development of symptomatic networks, longitudinal analysis becomes indispensable (Forbes et al., 2017; Funkhouser et al., 2020; Horváth et al., 2023; Robinaugh et al., 2020). Several studies have found a dynamically evolving association between symptoms accompanying problematic online short video watching, PIU, and depression (Jia et al., 2024; Qu et al., 2024; Zhao et al., 2023). In a two-wave study of PIU and depression, Zhao et al. (2023) reported that the PIU symptoms 'escape' and 'irritability' and the depression symptoms 'lack of energy' and 'guilty' (*Feeling bad about yourself, or that you are a failure or have let yourself or your family down*) were the most central over time. 'Guilty' in depression and 'escape' in PIU were the bridge symptoms, playing an important role in the cycle between PIU and depression.

In a four-wave longitudinal network analysis, Jia et al. (2024) reported that the PIU symptom 'time management' was the most influential node that predicted the depression symptoms over the first two study waves, while the PIU symptom 'tolerance' was the most influential in the later wave. In a two-wave network analysis of short video addiction and depression, the addiction symptom 'tolerance' and the depressive symptom 'anhedonia' were the most influential ones that predicted the subsequent depression symptoms over time. The addiction symptom 'conflict' and the depressive symptom 'sad mood' were the bridging symptoms (Qu et al., 2024).

For PSMU, a longitudinal network analysis study found that 'tolerance' and 'mood modification' were the most central symptoms in the network. Depression was less connected with PSMU than anxiety and stress (Tullett-Prado et al., 2023). Overall, using longitudinal network analysis, studies have identified the central, bridging, and influential symptoms (with high predictive power regarding subsequent symptoms) in the network of PIU and psychological distress over time. However, the observed inconsistency across studies, combined with the predominant focus on depression in the literature, warrants further investigation.

Overall, longitudinal network analysis studies on problematic internet use (PIU) and psychological distress have focused on three key aspects: (i) central and bridging nodes (or symptoms) between the two network communities over time, (ii) symptoms that predict subsequent symptoms across time points, and (iii) symptoms predicted by earlier manifestations. Consequently, the present study investigated the temporal dynamics of most central and bridging symptoms within the network, while specifically identifying influential (predictive) symptoms and susceptible (predicted) symptoms over time.

The Present Study

The relationship between PIU and psychological distress has been identified in theoretical models and empirical studies (e.g., Brand et al., 2019; Hussain et al., 2020; Lopes et al., 2022; Ostovar et al., 2016; Sonuga-Barke et al., 2024). Using network analysis, studies have detected the most central and influential symptoms or variables in the comorbidity network of PIU and psychological distress (e.g., L. Li et al., 2021; Qu et al., 2024; Wang et al., 2022). However, many network analysis studies have used the total scores of either PIU or psychological distress scales in their networks (e.g., Y. Li et al., 2023; Tullett-Prado et al., 2023) and did not focus on the specific symptoms or items. Longitudinal network analysis studies focusing on specific types of PIU and psychological distress are still needed to understand how particular problematic online activities, such as PSMU or POVW, are linked to psychological distress over time. Therefore, the present study selected two specific online activities (i.e., PSMU and POVW) as specific PIUs to examine.

PSMU and POVW were selected as specific types of PIU for several reasons. First, the inclusion of PSMU and POVW is grounded in their distinct behavioral mechanisms. PSMU is driven by social interaction and reassurance needs (e.g., fear of missing out and social comparison), whereby users engage in social communication (e.g., commenting, sharing) to fulfill belongingness and self-presentation needs (Billieux et al., 2015; Kuss & Griffiths,

2017). In contrast, POVW is characterized by relatively passive consumption (e.g., binge-watching *YouTube* videos or mukbang videos), which prioritizes escapism and mood regulation through unidirectional content consumption (Balakrishnan & Griffiths, 2017; Kircaburun et al., 2021). This dichotomy reflects the theoretical distinction between 'social media' (focused on networked interactions) and 'online video platforms' (focused on content dissemination). Because it is time-consuming to include all types of specific PIU in a three-wave longitudinal study, these two activities were chosen as being representative of specific online activities. Second, these two types of online applications were selected for their prevalence among Chinese internet users. According to the 55th Statistical Report on China's Internet Development, online social communication and online video consumption have been the two most frequently used types of applications in China (China Internet Network Information Center, 2025). The present study therefore focused on social media use and online video use as the most representative online activities for the Chinese population. Third, some online activities such as online gambling and online pornography websites are illegal or inaccessible in mainland China's internet context. Consequently, investigating such activities would be unsuitable because many Chinese participants likely lack access to or have little engagement in these behaviors.

Because the design features of social media and online video platforms differ (Flayelle et al., 2023), it is necessary to compare whether they are linked to psychological distress variables/symptoms in distinct ways. Moreover, users often engage in both activities simultaneously (e.g., scrolling social media while watching videos; Y. Chen et al., 2017), making it challenging to isolate their effects in natural settings. Examining them simultaneously provides a more ecologically valid understanding of how PIU manifests in daily life.

The anxiety, stress, and depression subscales of the DASS were used to assess psychological distress according to the tripartite model of mental health (Brown et al., 1997). The DASS operationalizes the tripartite model by assessing three core dimensions: the depression subscale (DASS-D) captures diminished positive affectivity, the anxiety subscale (DASS-A) reflects physiological hyperarousal, and the stress subscale (DASS-S) quantifies persistent negative emotional states (Brown et al., 1997).

It is also meaningful to use cross-lagged panel network (CLPN) analysis to detect symptoms that could predict others and have been predicted over time within the comorbidity mechanism of specific PIU and psychological distress. Therefore, the present study investigated the connections between the symptoms of two specific types of PIU (i.e., PSMU and POVW) and psychological distress over time using longitudinal network analysis. The node centrality and bridge centrality indices in the networks were estimated over time. The cross-lagged paths in the directed CLPN models were estimated to detect the symptoms with the highest influence (with high out-expected influence [out-EI] values) and susceptibility (with high in-expected influence [in-EI] values).

Moreover, previous studies have found that Chinese university students, especially first-year undergraduates, experience greater difficulties adapting to university life. These students also tend to exhibit more problematic smartphone use compared with Western students (Z. Yang et al., 2019). The association between mental health risks and IA among Chinese freshmen has been widely examined in the extant literature (e.g., Ni et al., 2009; Shan et al., 2021; Yu et al., 2025). However, longitudinal symptom-focused network analyses targeting this population remain scarce. Therefore, the present study focused specifically on first-year undergraduates.

There were four research questions: (i) What are the most central symptoms in the comorbidity network of specific PIU (PSMU and POVW) and psychological distress over time? (ii) What are the bridging symptoms in the comorbidity network over time? (iii) What are the most influential symptoms that predict the other symptoms over time in the CLPN model? (iv) What are the most susceptible symptoms that other symptoms predict over time in the CLPN model? Given the exploratory nature of the study, there were no specific hypotheses.

Methods

Participants and Procedure

Participants were first-year undergraduates recruited as part of a large project of specific PIU and psychological distress during 2021 and 2022. A total of 685 participants (mean age = 19.12 years, $SD = 0.92$), comprising 221 males and 464 females, completed three waves of surveys (T1: Time 1; T2: Time 2; and T3: Time 3).

Participants were recruited through convenience sampling. The survey link was distributed using the online survey platform www.wjx.cn where surveys could not be submitted unless all the questions had been answered. The

three waves of surveys were conducted from October 2021 to May 2022, with each wave spaced four months apart. Participants were asked to provide the last six digits of their phone number for data matching. The six digits were solely used for data matching and were not included in data analysis. It was not possible to trace individual identities using these digits. The inclusion criteria were being a first-year undergraduate student and voluntarily enrolling in the study and providing consent to do so.

A total of 834 surveys were initially completed. However, 12 were excluded from analysis due to invalid data, specifically uniform answering patterns (e.g., systematically selecting the same answer option across all survey items). Therefore, a total of 822 participants remained at the first time point (T1). Of these, 699 completed the second survey at T2, and 685 completed surveys at all three waves. At the start of each survey, all participants were provided with consent forms, from which informed consent was obtained, and participation in the study was voluntary. All responses were anonymous.

A four-month interval was determined for three key reasons. First, because the target participants were first-year undergraduate students, the surveys needed to be distributed between their formal enrollment (October) and summer vacation (June). Second, conducting three survey waves with two intervals provides methodological advantages over two waves with one interval because it allows for a better examination of temporal changes in specific PIU and psychological distress. Finally, comparing relationship dynamics across two distinct intervals offers richer insights into developmental trajectories than single-interval analyses, enhancing the analytical depth of longitudinal observations.

Measures

Bergen Social Media Addiction Scale (BSMAS)

PSMU was assessed using the six-item BSMAS (Andreassen et al., 2016; Chinese version: I.-H. Chen et al. (2020). The BSMAS items (e.g., *...used social media so much that it has had a negative impact on your job/studies*) – based on the components model of addiction (Griffiths, 2005) – are rated using a five-point Likert scale from 1 (*very rarely*) to 5 (*very often*). Each item in the BSMAS assesses a specific component in Griffiths' (2005) model. Scores range from 6 to 30 with higher scores indicating greater PSMU. The BSMAS has been proved to be reliable and valid in previous studies (e.g., I.-H. Chen et al., 2020; Y. Li et al., 2023; Peng & Liao, 2023). A recent meta-analysis evaluated the psychometric properties of the BSMAS, finding it to be a reliable and valid tool for assessing social media addiction across diverse populations. The evidence supports its unidimensionality, internal consistency, and associations with related constructs such as anxiety and depression (Bottaro et al., 2025). The Cronbach's alpha values for the three waves were .85 (T1), .85 (T2), and .86 (T3).

Problematic Online Video Watching Scale (POVWS)

POVW was assessed using the six-item POVWS adapted from the BSMAS (Andreassen et al., 2016; Chinese version: Yan et al., 2023). The POVWS items (e.g., *...tried to cut down on watching online videos without success*) are rated using a five-point Likert scale from 1 (*very rarely*) to 5 (*very often*). Each item in the POVWS assesses a specific component in Griffiths' (2005) model. Scores range from 6 to 30 with higher scores indicating greater POVW. The POVWS has been shown to be reliable and valid in previous studies (e.g., Yan et al., 2023). The Cronbach's alpha values for the three waves were .77 (T1), .82 (T2), and .82 (T3).

Depression Anxiety Stress Scale-21 (DASS-21)

Psychological distress was assessed using the 21-item DASS-21 (Lovibond & Lovibond, 1995; Chinese version: Gong et al., 2010). The scale comprises three subscales (*depression*, *anxiety* and *stress*) each consisting of seven items. The items (see Table 2) are rated from 0 (*did not apply to me at all*) to 3 (*applied to me very much, or most of the time*). Scores range from 0 to 21 on each subscale with higher scores indicating greater psychological distress. The DASS-21 has been proved to be reliable and valid in previous studies (e.g., Y. Li et al., 2023; Peng & Liao, 2023; Zanon et al., 2020). A systematic review by Lee et al. (2019) found that the DASS-21 demonstrates strong reliability and validity. The Cronbach's alpha values for the three waves were: depression (T1: .84, T2: .85, T3: .86), anxiety (T1: .79, T2: .82, T3: .82), and stress (T1: .78, T2: .82, T3: .82).

Table 2. *Descriptive Statistics and Abbreviations for the Items.*

Component	Label	Items	Mean	SD
Depression, Anxiety and Stress Scale-21				
Dry mouth	T1A1: Time 1 Anxiety 1	I was aware of dryness of my mouth	0.82	0.78
	T2A1: Time 2 Anxiety 1		0.74	0.76
	T3A1: Time 3 Anxiety 1		0.73	0.78
Breathing difficulty	T1A2: Time 1 Anxiety 2	I experienced breathing difficulty (e.g., excessively rapid breathing, breathlessness in the absence of physical exertion)	0.41	0.65
	T2A2: Time 2 Anxiety 2		0.39	0.64
	T3A2: Time 3 Anxiety 2		0.40	0.64
Trembling	T1A3: Time 1 Anxiety 3	I experienced trembling (e.g., in the hands)	0.44	0.67
	T2A3: Time 2 Anxiety 3		0.44	0.68
	T3A3: Time 3 Anxiety 3		0.40	0.64
Worried	T1A4: Time 1 Anxiety 4	I was worried about situations in which I might panic and make a fool of myself	1.72	0.93
	T2A4: Time 2 Anxiety 4		1.58	0.95
	T3A4: Time 3 Anxiety 4		1.54	0.94
Panic	T1A5: Time 1 Anxiety 5	I felt I was close to panic	0.46	0.66
	T2A5: Time 2 Anxiety 5		0.48	0.70
	T3A5: Time 3 Anxiety 5		0.51	0.71
Heart aware	T1A6: Time 1 Anxiety 6	I was aware of the action of my heart in the absence of physical exertion (e.g., sense of heart rate increase, heart missing a beat)	0.46	0.74
	T2A6: Time 2 Anxiety 6		0.49	0.73
	T3A6: Time 3 Anxiety 6		0.53	0.74
Scared	T1A7: Time 1 Anxiety 7	I felt scared without any good reason	0.54	0.72
	T2A7: Time 2 Anxiety 7		0.48	0.69
	T3A7: Time 3 Anxiety 7		0.53	0.72
No positive	T1D1: Time 1 Depression 1	I couldn't seem to experience any positive feeling at all	0.60	0.73
	T2D1: Time 2 Depression 1		0.67	0.79
	T3D1: Time 3 Depression 1		0.65	0.75
No initiative	T1D2: Time 1 Depression 2	I found it difficult to work up the initiative to do things	0.89	0.80
	T2D2: Time 2 Depression 2		1.04	0.85
	T3D2: Time 3 Depression 2		1.15	0.88
Not looking forward	T1D3: Time 1 Depression 3	I felt that I had nothing to look forward to	0.67	0.83
	T2D3: Time 2 Depression 3		0.78	0.85
	T3D3: Time 3 Depression 3		0.82	0.85
Down-hearted	T1D4: Time 1 Depression 4	I felt down-hearted and blue	0.81	0.81
	T2D4: Time 2 Depression 4		0.82	0.76
	T3D4: Time 3 Depression 4		0.84	0.78
Not enthusiastic	T1D5: Time 1 Depression 5	I was unable to become enthusiastic about anything	0.50	0.74
	T2D5: Time 2 Depression 5		0.59	0.76
	T3D5: Time 3 Depression 5		0.56	0.77
Worthless person	T1D6: Time 1 Depression 6	I felt I wasn't worth much as a person	0.27	0.59
	T2D6: Time 2 Depression 6		0.32	0.64
	T3D6: Time 3 Depression 6		0.32	0.65
Meaningless of life	T1D7: Time 1 Depression 7	I felt that life was meaningless	0.34	0.67
	T2D7: Time 2 Depression 7		0.38	0.70
	T3D7: Time 3 Depression 7		0.39	0.70
No wind down	T1S1: Time 1 Stress 1	I found it hard to wind down	0.92	0.74
	T2S1: Time 2 Stress 1		0.88	0.74
	T3S1: Time 3 Stress 1		0.89	0.74

Component	Label	Items	Mean	SD
Overreactive	T1S2: Time 1 Stress 2	I tended to over-react to situations	0.67	0.76
	T2S2: Time 2 Stress 2		0.65	0.76
	T3S2: Time 3 Stress 2		0.68	0.74
Nervous energy	T1S3: Time 1 Stress 3	I felt that I was using a lot of nervous energy	1.08	0.84
	T2S3: Time 2 Stress 3		1.00	0.82
	T3S3: Time 3 Stress 3		1.15	0.85
Agitated	T1S4: Time 1 Stress 4	I found myself getting agitated	0.87	0.79
	T2S4: Time 2 Stress 4		0.83	0.81
	T3S4: Time 3 Stress 4		0.87	0.78
No relaxing	T1S5: Time 1 Stress 5	I found it difficult to relax	0.84	0.84
	T2S5: Time 2 Stress 5		0.80	0.83
	T3S5: Time 3 Stress 5		0.86	0.83
Intolerant	T1S6: Time 1 Stress 6	I was intolerant of anything that kept me from getting on with what I was doing	1.04	0.86
	T2S6: Time 2 Stress 6		0.97	0.86
	T3S6: Time 3 Stress 6		0.98	0.86
Touchy	T1S7: Time 1 Stress 7	I felt that I was rather touchy	0.76	0.80
	T2S7: Time 2 Stress 7		0.75	0.81
	T3S7: Time 3 Stress 7		0.75	0.81
Bergen Social Media Addiction Scale				
Salience	T1PSMU1: Time 1 Problematic Social Media Use 1	... spent a lot of time thinking about social media or planned use of social media?	3.14	1.10
	T2PSMU1: Time 2 Problematic Social Media Use 1		3.13	1.06
	T3PSMU1: Time 3 Problematic Social Media Use 1		3.18	1.01
Craving/tolerance	T1PSMU2: Time 1 Problematic Social Media Use 2	... felt an urge to use social media more and more?	3.13	1.13
	T2PSMU2: Time 2 Problematic Social Media Use 2		3.12	1.06
	T3PSMU2: Time 3 Problematic Social Media Use 2		3.11	1.05
Mood modification	T1PSMU3: Time 1 Problematic Social Media Use 3	... used social media to forget about personal problems?	2.33	1.04
	T2PSMU3: Time 2 Problematic Social Media Use 3		2.46	0.99
	T3PSMU3: Time 3 Problematic Social Media Use 3		2.58	1.02
Relapse/loss of control	T1PSMU4: Time 1 Problematic Social Media Use 4	... tried to cut down on the use of social media without success?	2.55	1.13
	T2PSMU4: Time 2 Problematic Social Media Use 4		2.65	1.05
	T3PSMU4: Time 3 Problematic Social Media Use 4		2.70	1.05
Withdrawal	T1PSMU5: Time 1 Problematic Social Media Use 5	... become restless or troubled if you have been prohibited from using social media?	2.48	1.11
	T2PSMU5: Time 2 Problematic Social Media Use 5		2.51	1.09
	T3PSMU5: Time 3 Problematic Social Media Use 5		2.54	1.06
Conflict/functional impairment	T1PSMU6: Time 1 Problematic Social Media Use 6	... used social media so much that it has had a negative impact on your job/studies?	2.31	0.99
	T2PSMU6: Time 2 Problematic Social Media Use 6		2.47	1.00
	T3PSMU6: Time 3 Problematic Social Media Use 6		2.57	1.03

Component	Label	Items	Mean	SD
Problematic Online Video Watching Scale				
Salience	T1POVW1: Time 1 Problematic Online Video Use 1		3.24	0.93
	T2POVW1: Time 2 Problematic Online Video Use 1	... spent a lot of time thinking about online videos or planned watching of online videos?	3.41	0.93
	T3POVW1: Time 3 Problematic Online Video Use 1		3.50	0.89
Craving/tolerance	T1POVW2: Time 1 Problematic Online Video Use 2		2.98	0.96
	T2POVW2: Time 2 Problematic Online Video Use 2	... felt an urge to watch online videos more and more?	3.16	0.94
	T3POVW2: Time 3 Problematic Online Video Use 2		3.27	0.92
Mood modification	T1POVW3: Time 1 Problematic Online Video Use 3		2.48	1.01
	T2POVW3: Time 2 Problematic Online Video Use 3	... watched online videos to forget about personal problems?	2.70	0.97
	T3POVW3: Time 3 Problematic Online Video Use 3		2.89	0.97
Relapse/loss of control	T1POVW4: Time 1 Problematic Online Video Use 4		2.58	1.08
	T2POVW4: Time 2 Problematic Online Video Use 4	... tried to cut down on watching online videos without success?	2.76	0.98
	T3POVW4: Time 3 Problematic Online Video Use 4		2.85	0.98
Withdrawal	T1POVW5: Time 1 Problematic Online Video Use 5		2.08	1.03
	T2POVW5: Time 2 Problematic Online Video Use 5	... become restless or troubled if you have been prohibited from watching online videos?	2.29	1.03
	T3POVW5: Time 3 Problematic Online Video Use 5		2.37	1.01
Conflict/functional impairment	T1POVW6: Time 1 Problematic Online Video Use 6		2.34	0.98
	T2POVW6: Time 2 Problematic Online Video Use 6	... watched online videos so much that it has had a negative impact on your job/studies?	2.61	1.02
	T3POVW6: Time 3 Problematic Online Video Use 6		2.78	1.03

Note. $N = 685$ for each time point. The components of the PSMU and POVW items were obtained from Andreassen et al. (2016); the components of the DASS-21 items were obtained from Van den Bergh et al. (2021).

Data analysis

The present study conducted all analyses, including cross-lagged network analysis, using R v4.2.2. The R packages: bootnet v1.6 (Epskamp et al., 2018), networktools v1.6.0 (Jones, 2025), and glmnet v4.1.8 (Friedman et al., 2010) were used for estimating network models, while qgraph v1.9.8 (Epskamp et al., 2012) was used for visualizing these models. The tidyverse v2.0.0 (Wickham et al., 2019) was also used for data analysis.

Cross-Sectional Data Network Modelling

To begin with, and because all variables were considered continuous, the network model was constructed using the undirected Gaussian Graphical Model (GGM) within pairwise Markov random fields (PMRFs). To ensure the model remained both parsimonious and sparse, the least absolute shrinkage and selection operator (LASSO) regularization and extended Bayesian information criterion (EBIC) were utilized for model selection (hyper tuning parameter = 0.5). Each of the three models comprised the same 33 nodes but included 229, 211, and 228 edges, respectively. The centrality indices of strength, closeness, and betweenness were calculated to assess the influence of individual nodes within the network.

Centrality indices help determine the position and role of nodes within the network. Strength refers to the number of direct connections a node has, with a higher standardized strength value indicating more direct links to other nodes. Closeness measures the inverse of the total shortest distance from one node to all others, where a higher standardized closeness value indicates that the node can reach all other nodes more swiftly. Betweenness reflects how often a node lies on the shortest path between any two other nodes, with a higher standardized betweenness

value indicating greater activity or influence between other nodes. Bridge strength and bridge expected influence indicate the number and strength of a node's connections to nodes in other clusters, bridge closeness indicates how easily a node can reach all nodes in other clusters, and bridge betweenness indicates how often a node appears on the shortest paths between different clusters (Isvoranu et al., 2022).

Cross-Lagged Panel Networks Models

When constructing cross-lagged panel network (CLPN) models, model building was separately conducted for $T1 \rightarrow T2$ and $T2 \rightarrow T3$. This approach controlled for the autoregressive effect of each node while accounting for associations both within and across time points. It estimates the influence of a single node at one time point on all other nodes at the subsequent time point, allowing for the exploration of symptom prediction pathways within the comorbidity networks of specific PIU and psychological distress, $T1$, $T2$, and $T3$. To identify the best model, a simulation study compared the performance of regularization parameter selection in the network model, finding that cross-validation displayed high sensitivity and low specificity across various conditions (Wysocki & Rhemtulla, 2021). Consequently, LASSO with 10-fold cross-validation tuning parameter selection was used to regularize the regression coefficients.

The CLPN model was used for the following reasons: (i) symptom-level focus: longitudinal associations between specific PIU and psychological distress were analyzed at the individual symptom level. Unlike traditional latent variable-based structural equation models (e.g., panel-LVGVAR), CLPN avoids assuming unobserved constructs, enabling granular tracking of symptom dynamics (Epskamp, 2020); (ii) symptom-level measurement: The tools used assessed symptoms through continuous single-item scores, aligning with CLPN's framework. Each item represents an elemental node in a dynamic network, consistent with the network analysis perspective of focusing on symptom interactions; (iii) non-stationary data compatibility: CLPN accommodates temporal heterogeneity. The present study's data show shifting dynamics. More specifically, PIU symptoms dominate early ($T1$ to $T2$), while emotional distress drives later changes ($T2$ to $T3$), mirroring the I-PACE model's progression. Panel-LVGVAR requires stationarity and measurement invariance, which the evolving data in the present study violate; (iv) network centrality insights: CLPN quantifies in- and out-expected influence, pinpointing intervention targets. Panel-LVGVAR focuses on latent constructs, lacking this symptom-level precision; and (v) validation in similar contexts: CLPN has proven effective in modeling symptom-level pathways and comorbidity evolution (e.g., Funkhouser et al., 2020; Jia et al., 2024), directly addressing the present study's research aims. In summary, CLPN's symptom-level granularity, flexibility for non-stationary data, and alignment with the present study's design and theory make it the optimal choice.

Centrality Estimation

Because cross-lagged networks are directed, unlike the undirected models used in cross-sectional data network modelling, expected influence (EI) is employed to estimate centrality in the network. In directed networks, EI is categorized into out-expected influence (out-EI) and in-expected influence (in-EI), indicating a node's ability to predict other nodes and its capacity to be predicted by other nodes within the network.

Stability Estimation

The stability and accuracy of edge estimates in the network model were evaluated using a bootstrapping method. First, non-parametric bootstrapped confidence intervals (CIs) were calculated for edge weights to assess their accuracy. Then, case-dropping subset bootstrapping was conducted to evaluate the stability of centrality indices, resulting in correlation stability (CS) coefficients. These coefficients indicate the degree to which a large proportion (ideally at least 50%) of cases (for 95%) can be removed while maintaining a correlation of at least 0.70 between centrality measures in the full sample and the case-dropping subsets (Isvoranu et al., 2022, p.139).

Ethics

The present study was approved by the Ethics Committee of the first author's university. All procedures adhered to the ethical standards outlined in the Declaration of Helsinki. Written informed consent was obtained from each individual before their participation commenced. The study was not pre-registered and the data are available from the corresponding author upon reasonable request.

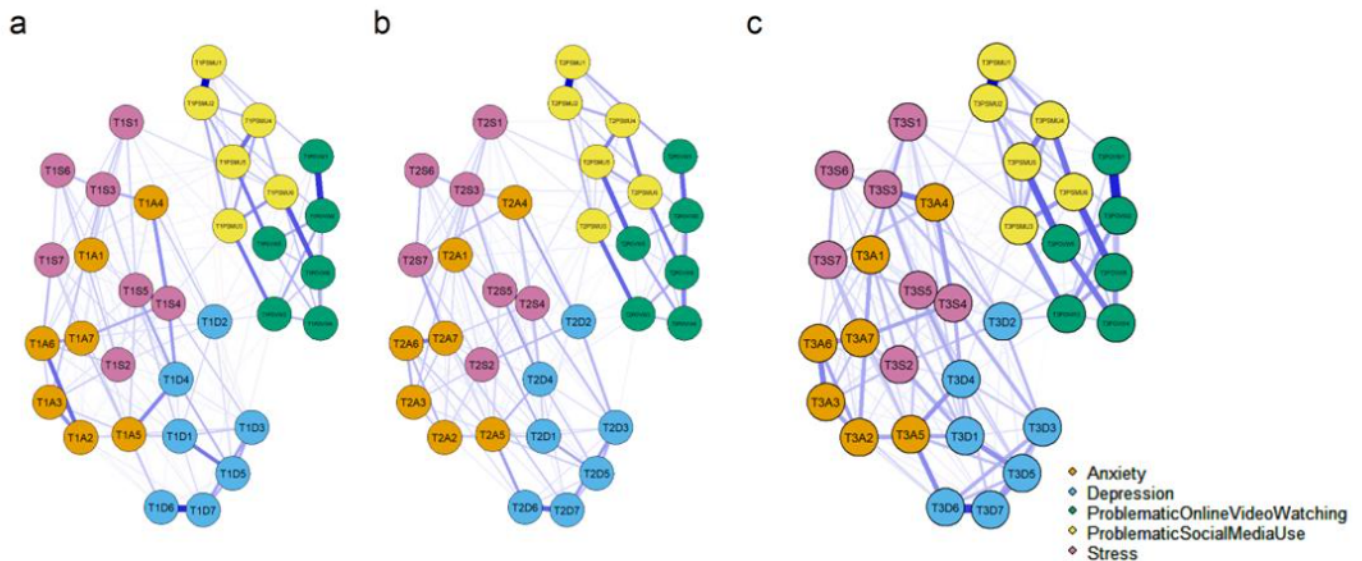
Results

Cross-Sectional Data Network Model

Descriptive Statistics

Table 2 provides the descriptive statistics and abbreviations for each node, while Figure 1 illustrates the comorbidity network model across the three time points. Each node in the network represents items from various scales. The weights matrix is provided in Supplementary Material S1. Symptoms/items related to POVW, PSMU, stress, anxiety, and depression were organized into distinct clusters within the network plot. All variables in the three waves were normally distributed (see the descriptive statistics in S2).

Figure 1. Cross-Sectional Data Network Models at Three Time Point.



Note. a, T1 time point; b, T2 time point; c, T3 time point. Blue lines represent positive connections, and red lines represent negative connections.

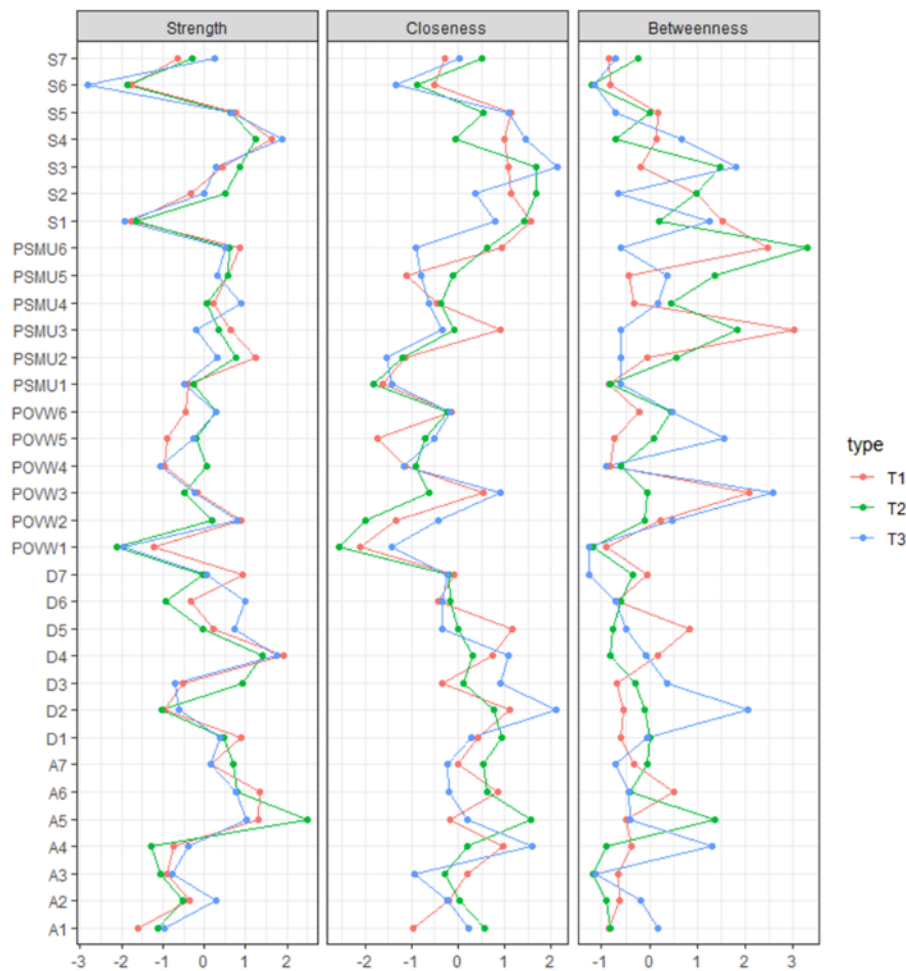
Potential item overlap between PSMU and POVW was evaluated using the 'goldbricker' function in R package networktools (threshold = 0.75 as default). For the three waves of data, the analysis did not detect suggested reductions between PSMU and POVW items. Only items within PSMU or POVW were shown in the 'goldbricker' results of 'suggested reductions' (see S3). Item correlations were also calculated as shown in S4. Most of the correlation coefficients between PSMU and POVW items were low (<0.50).

Attrition analyses did not show any significant differences between participants who dropped out (16.7%) and those who took part in all three surveys when considering all the variables: PSMU: $t(820) = -0.25$, $p = .801$; POVW: $t(820) = -1.60$, $p = .110$; psychological distress: total score: $t(820) = 1.21$, $p = .226$; stress: $t(820) = 1.00$, $p = .319$; depression: $t(820) = 1.24$, $p = .214$; and anxiety: $t(820) = 1.05$, $p = .295$.

Centrality Estimation

The centrality estimation for the cross-sectional data network model includes 'strength', 'closeness', and 'betweenness', as displayed in Figure 2. At T1, the three symptoms with the highest strength values were 'downhearted' from depression (D4, standardized coefficient [SC] = 1.91), 'agitated' from stress (S4, SC = 1.64), and 'heart aware' from anxiety (A6, SC = 1.35). Additionally, problematic internet use symptoms 'craving/tolerance' (PSMU2, SC = 0.88) and 'conflict/functional impairment' from PSMU (PSMU6, SC = 0.87), along with 'craving/tolerance' from POVW (POVW2, SC = 0.88), were among the top ten ranked symptoms.

Figure 2. Standardized Centrality Indices for the Cross-Sectional Data Network Model Across Three Time Point.



At T2, the symptoms with the highest strength were 'panic' from anxiety (A5, SC = 2.48), 'down-hearted' from depression (D2, SC = 1.41), and 'agitated' from stress (S4, SC = 1.25). The symptoms PSMU2 (SC = 0.78) and PSMU6 (SC = 0.60), which appeared in the top ten at T1, were also present at T2. At T3, the top three symptoms in terms of strength were the 'agitated' from Stress (S4, SC = 1.88), 'down-hearted' from depression (D4, SC = 1.75), and 'panic' from 'anxiety' (A5, SC = 1.01). Among the top ten PIU symptoms at T3, some were the same as at T1: PSMU4 (SC = 0.89), POVW2 (SC = 0.80), and PSMU6 (SC = 0.50).

The strength results indicate that in the network models at all three time points, the symptoms most central, or most interconnected with other symptoms, were those associated with depression, anxiety, and stress. The 'down-hearted' symptom from depression and the 'agitated' symptom from stress consistently ranked among the top three at all three time points, suggesting that these two symptoms may be consistently central within the comorbidity network of PSMU, POVW, and psychological distress, meaning they are the most connected to other symptoms.

In the results of closeness, the PSMU6 symptom 'conflict/functional impairment' appeared among the top ten in the network model at T1 (SC = 0.95) and T2 (SC = 0.64). Additionally, the 'no wind down' symptom (S1) and 'overreactive' symptom (S2) in stress were among the top five in closeness at T1 (SC = 1.58 and 1.13) and T2 (SC = 1.42 and 1.70). The 'nervous energy' symptom (S3) in stress appeared in the top five at T2 (SC = 1.67) and T3 (SC = 2.14). The 'no initiative' symptom (D2) in depression appeared in the top five at T1 (SC = 1.12) and T3 (SC = 2.12). This indicates that these symptoms of stress and depression connect more quickly to other symptoms, suggesting that they may play a significant role in connecting and influencing other symptoms within the network model.

With regards to betweenness, the 'mood modification' symptom (PSMU3) and 'conflict/functional impairment' symptom (PSMU6) in PSMU had a significant impact at T1 (SC = 3.00 and 2.47) and T2 (SC = 1.83 and 3.30). At T3, the most impactful symptoms were the 'mood modification' symptom (POVW3) in POVW and the 'no initiative' symptom (D2) in depression. This suggests that these symptoms, especially 'mood modification', frequently

appear on the pathways linking other symptoms, indicating that this symptom is a key factor in the pathways connecting other symptoms.

Bridge Centrality Estimation

To identify bridge symptoms within the comorbidity network, all items were divided into two clusters: ‘problematic internet use’ (including PSMU and POVW) and ‘psychological distress’ (anxiety, depression, and stress; Figures 3,4 and 5). The results suggested that the ‘conflict/functional impairment’ (PSMU6) and ‘mood modification’ (PSMU3) symptoms in PSMU may play a crucial role in connecting the comorbidity network to the specific PIU cluster. Similar results were found for these symptoms in POVW (with high bridge strength and bridge betweenness values at T1 and T2, see Supplementary material). Additionally, the ‘no wind down’ (S1) and ‘overreactive’ (S2) symptoms in stress played a significant role in linking the specific PIU cluster (with higher bridge closeness values across all three time points), indicating that these nodes facilitate easier access to all symptom nodes in the specific PIU cluster.

Figure 3. Standardized Centrality Indices for the Cross-Sectional Data Network Model of Time 1.

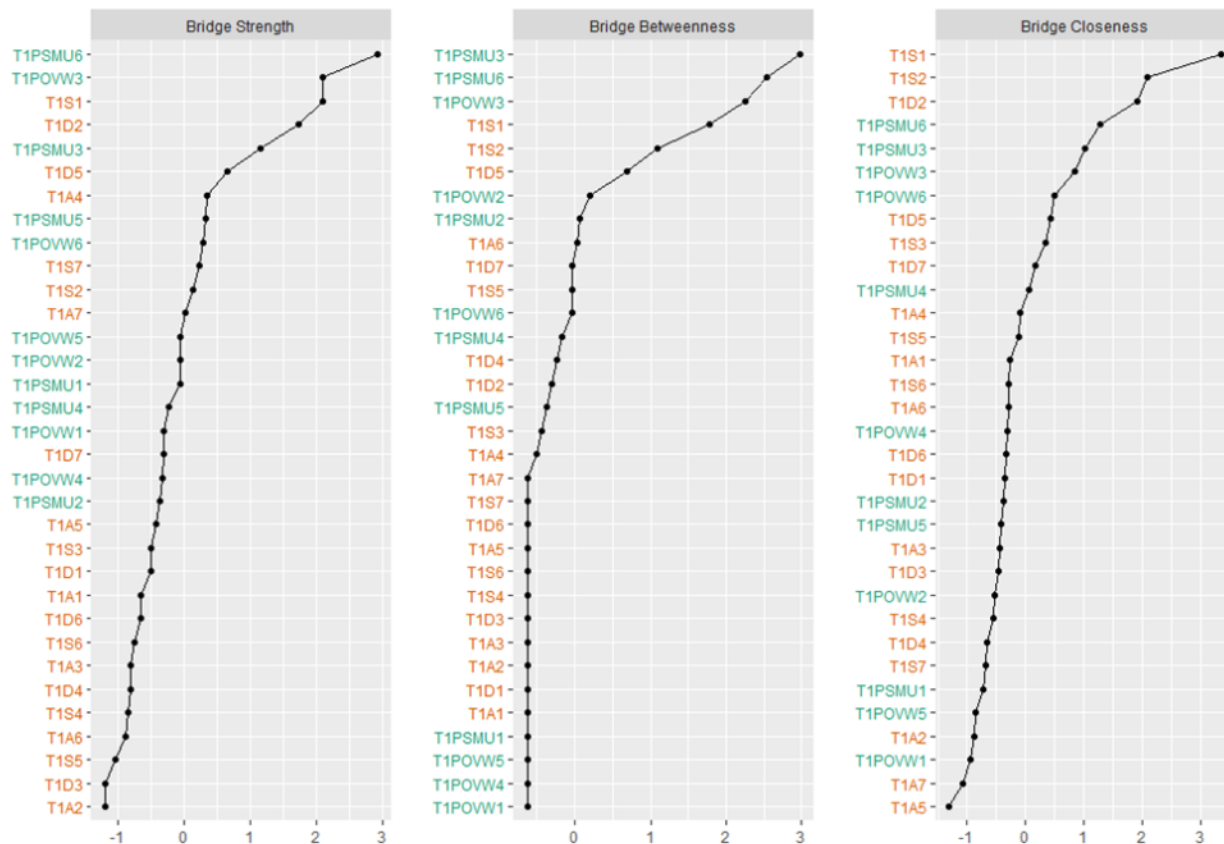


Figure 4. Standardized Centrality Indices for the Cross-Sectional Data Network Model of Time 2.

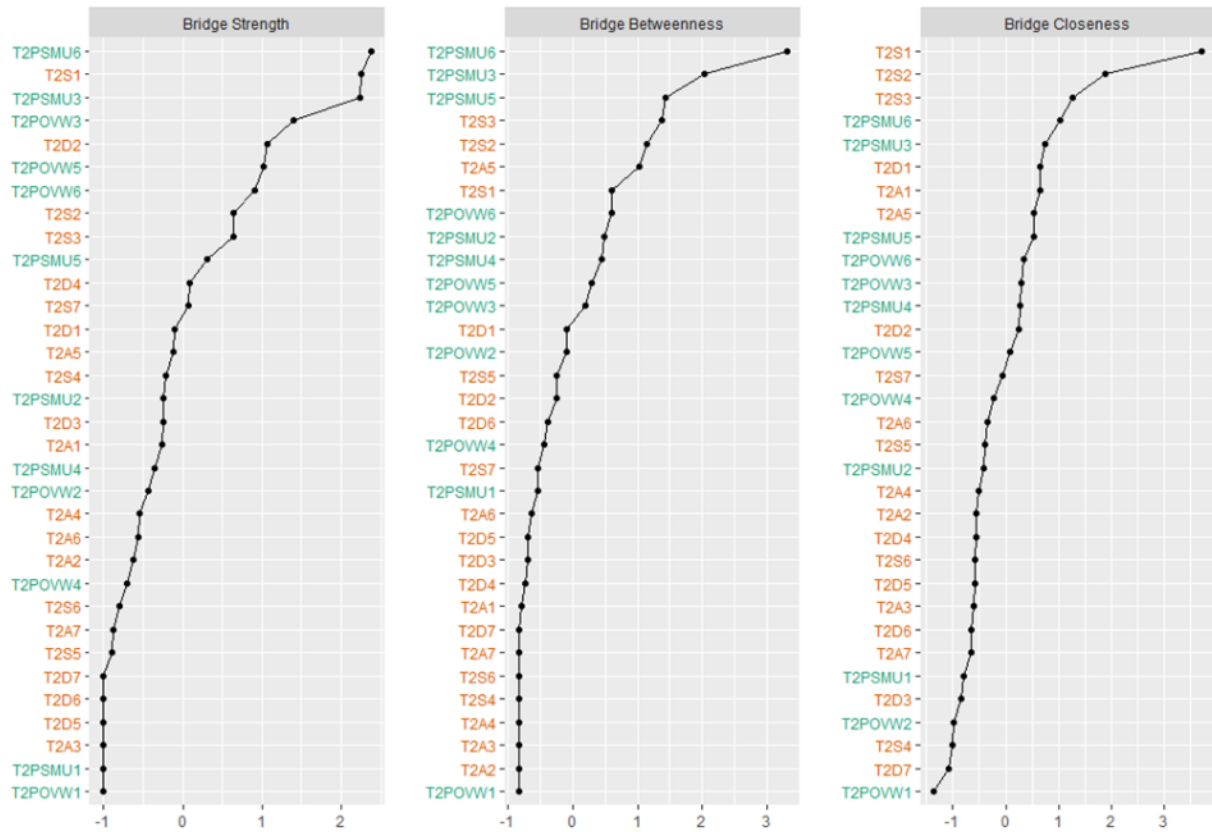
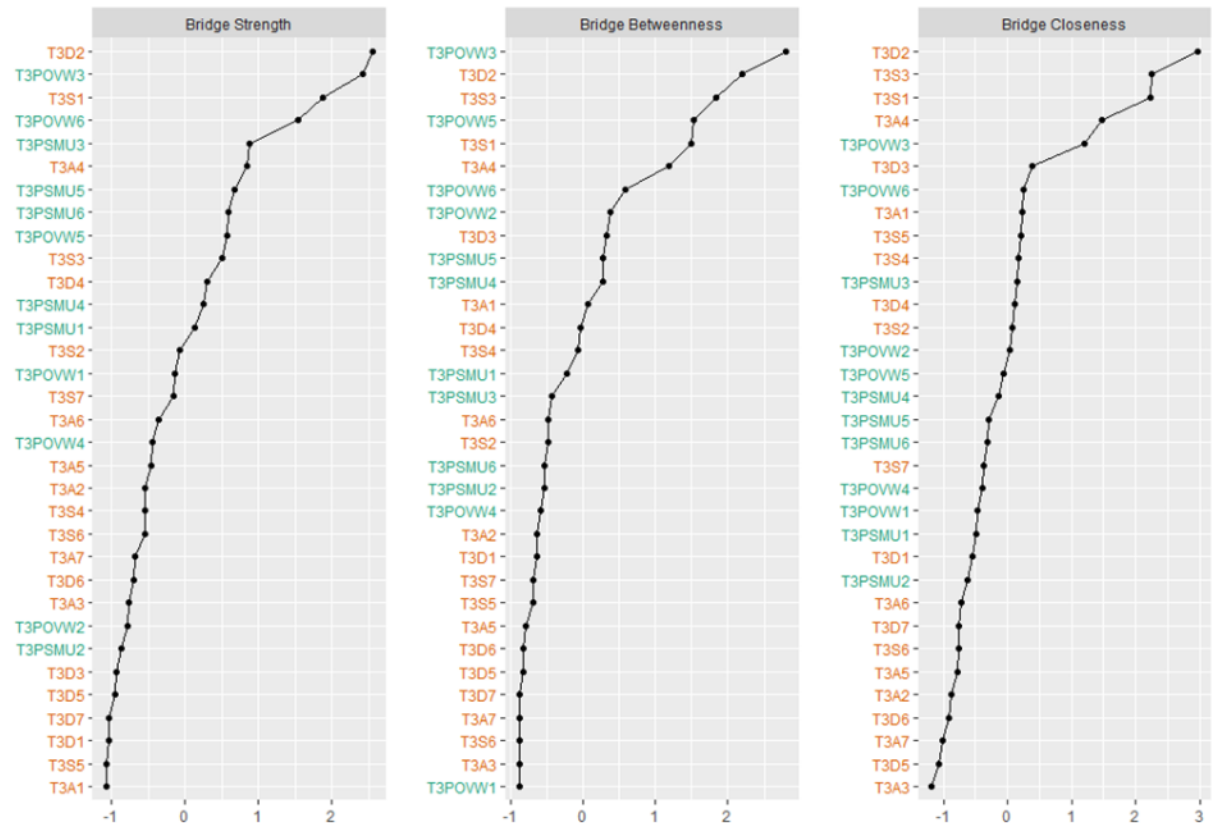


Figure 5. Standardized Centrality Indices for the Cross-Sectional Data Network Model of Time 3.



Accuracy and Stability Estimations

Supplementary Material S5 show the bootstrapped confidence intervals (CIs) for edge weights at T1, T2, and T3, with red indicating edge weight values and grey representing 95% CIs. The stability results for the three time points were as follows: T1 betweenness CS ($\text{cor} = 0.7$; a correlation of at least 0.7 between the original and bootstrapped

samples) = 0.05, closeness CS (cor = 0.7) = 0.128, strength CS (cor = 0.7) = 0.594; T2 betweenness CS (cor = 0.7) = 0, closeness CS (cor = 0.7) = 0.128, strength CS (cor = 0.7) = 0.672; T3 betweenness CS (cor = 0.7) = 0.128, closeness CS (cor = 0.7) = 0.206, strength CS (cor = 0.7) = 0.672 (Supplementary material S6). Apart from the poor stability of betweenness, the network's strength demonstrated acceptable stability. Bootstrapped difference tests ($\alpha = .05$) between node strength are shown in S7.

Network Comparison Tests Between Genders

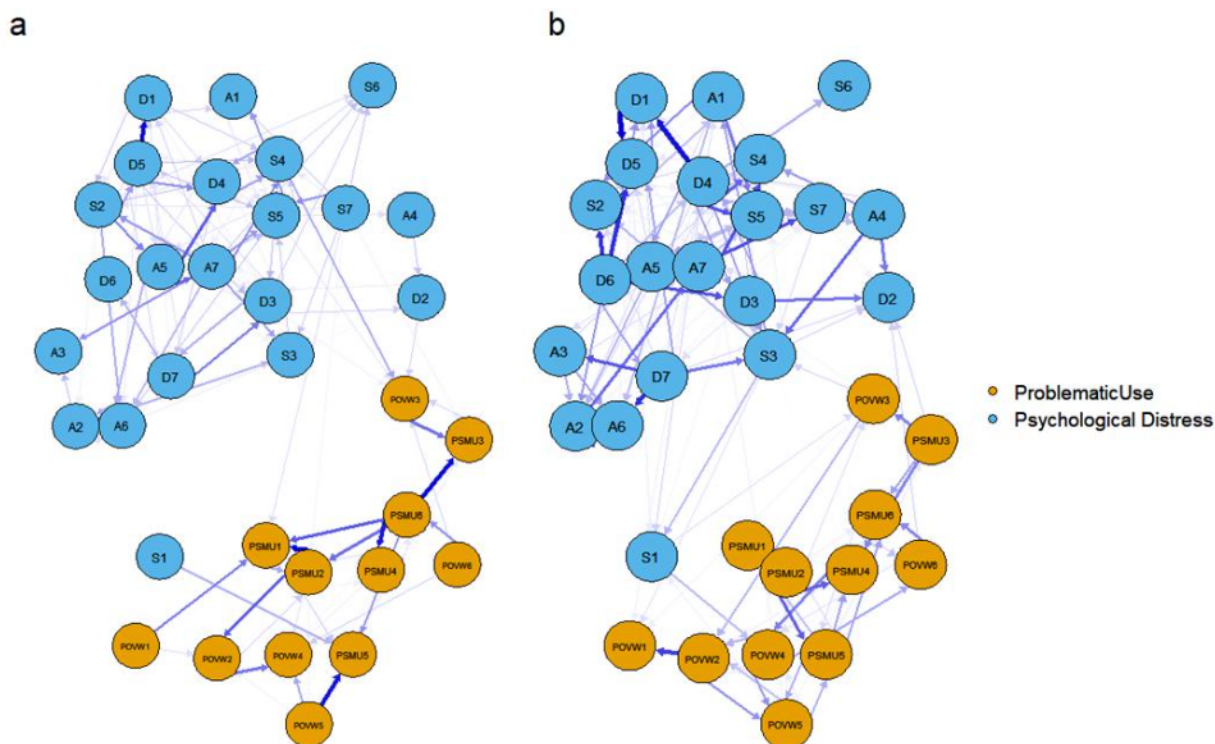
NCTs were conducted between females and males at the three time points. Network invariance tests show that there was no significant difference in network structure between genders at T1 (test statistic $M = 0.18$, $p = .800$), T2 (test statistic $M = 0.20$, $p = .485$), and T3 (test statistic $M = 0.18$, $p = .766$). Moreover, global strength invariance tests showed that there was no significant difference in node strength between genders at T1 (test statistic $S = 0.51$, $p = .373$), T2 (test statistic $S = 0.10$, $p = .766$), and T3 (test statistic $S = 0.12$, $p = .754$).

Cross-Lagged Panel Network Model

Network Structure Estimation

The symptom networks from T1→T2 and T2→T3 were estimated using cross-lagged network models (see Figure 6). Blue arrows in the figure indicate positive predictions, while red arrows indicate negative predictions, with autoregressive effects removed. The T1→T2 cross-lagged network contained 33 nodes and 133 non-zero edges, with a mean weight of 0.005. Similarly, the T2→T3 network also contained 33 nodes, but with 152 non-zero edges and the same mean weight of 0.005.

Figure 6. Cross-Lagged Network Models.



Note. a) symptom networks from T1→T2; b) symptom networks from T2→T3.

Centrality Estimation

Centrality estimates for the cross-lagged networks are shown in Figure 7 and Table 3. During the T1→T2 period, the top three symptoms for in-expected influence (in-EI) were 'salience' (PSMU1, SC = 2.12) and 'withdrawal' (PSMU5, SC = 1.49) symptoms from PSMU, and the 'down-hearted' symptom (D4) from depression. For out-expected influence (out-EI), the top three symptoms were 'conflict/functional impairment' symptom (PSMU6, SC = 2.80) from PSMU, the 'scared' symptom (A7, SC = 2.34) from anxiety, and the 'not enthusiastic' symptom (D5, SC = 1.93) from depression. During the T2→T3 period, the top three symptoms for in-EI were the 'not enthusiastic' symptom (D5, SC = 2.04) from depression, the 'agitated' symptom (S4, SC = 1.67) from stress, and the 'heart aware' symptom (A6, SC = 1.45) from anxiety. For out-EI, the top three symptoms were the 'down-hearted' (D4, SC = 3.39), 'worthless person' (D6, SC = 2.58), and 'meaningless of life' (D7, SC = 1.52) symptoms from depression. The high out-EI and in-EI suggest that these symptoms are central in predicting other symptoms at the next time point and are also key in being predicted by other symptoms.

Figure 7. Standardized Centrality Indices for the Cross-Lagged Network Models.

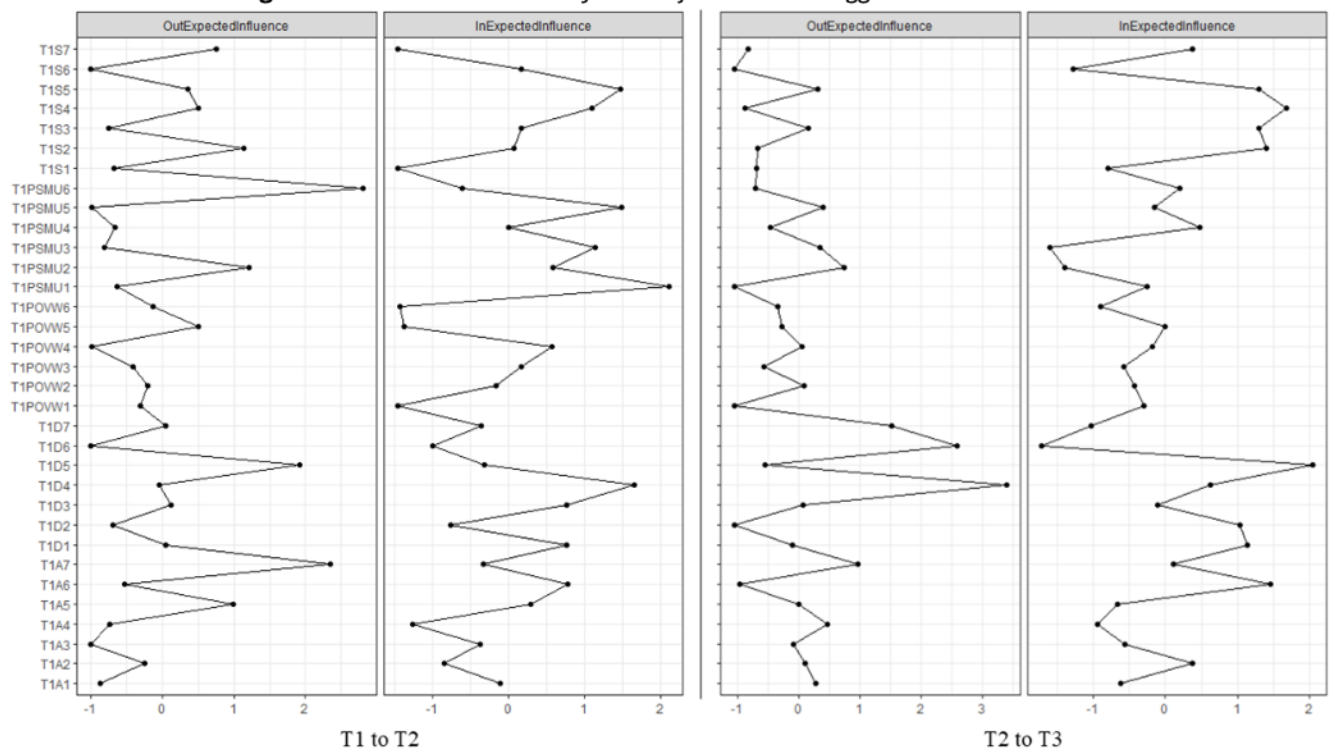


Table 3. *Standardized Centrality Indices for the Cross-Lagged Network Model.*

Node	T1→T2		T2→T3	
	Standardized in-EI	Standardized out-EI	Standardized out-EI	Standardized in-EI
A1	-0.12	-0.87	0.27	-0.62
A2	-0.85	-0.25	0.10	0.38
A3	-0.37	-1.00	-0.09	-0.56
A4	-1.26	-0.74	0.47	-0.93
A5	0.29	0.98	0.00	-0.67
A6	0.78	-0.53	-0.96	1.45
A7	-0.33	2.34	0.97	0.11
D1	0.77	0.05	-0.11	1.13
D2	-0.77	-0.70	-1.06	1.03
D3	0.77	0.12	0.06	-0.11
D4	1.66	-0.05	3.39	0.62
D5	-0.31	1.93	-0.56	2.04
D6	-1.00	-1.00	2.58	-1.72
D7	-0.36	0.05	1.52	-1.03
PSMU1	2.12	-0.64	-1.06	-0.25
PSMU2	0.59	1.21	0.74	-1.39
PSMU3	1.14	-0.81	0.34	-1.60
PSMU4	0.01	-0.66	-0.47	0.47
PSMU5	1.49	-1.00	0.39	-0.14
PSMU6	-0.62	2.80	-0.71	0.20
POVW1	-1.46	-0.31	-1.06	-0.29
POVW2	-0.16	-0.20	0.07	-0.43
POVW3	0.17	-0.41	-0.57	-0.57
POVW4	0.57	-0.99	0.04	-0.18
POVW5	-1.38	0.51	-0.28	0.00
POVW6	-1.44	-0.13	-0.35	-0.90
S1	-1.46	-0.67	-0.70	-0.80
S2	0.07	1.13	-0.67	1.40
S3	0.17	-0.76	0.16	1.30
S4	1.10	0.51	-0.88	1.67
S5	1.48	0.35	0.30	1.30
S6	0.17	-1.00	-1.06	-1.28
S7	-1.46	0.76	-0.82	0.37

Stability Analysis

The bootstrapping results for the edges in the T1→T2 and T2→T3 periods (bootstrapped samples = 1,500) are shown in Supplementary material S8, indicating that some edges may have lower accuracy. The results from case-dropping subset bootstrapping (bootstrapped samples = 1,000) for centrality stability show that in the T1→T2 network model, both in-EI and out-EI had CS (cor = 0.7) = 0.128. In the T2→T3 period, the CS (cor = 0.7) for in-EI and out-EI were 0 and 0.439, respectively.

Discussion

Summary of the Results

The present study investigated how specific types of PIU and psychological distress interact over time through longitudinal comorbidity network models. The depression and stress symptoms, 'down-hearted' (D4) and 'agitated' (S4), were consistently the most central symptoms from T1 to T3. PSMU symptoms 'mood modification' and 'conflict/functional impairment' were the key bridging symptoms in the network in T1 and T2, while the depression symptom 'no initiative' (D2) became the key bridging symptom in T3. In the CLPN models, the specific PIU symptoms were the most influential and susceptible nodes from T1 to T2, while the psychological distress symptoms became the major issues from T2 to T3.

Relationship With Previous Findings and Implications

The findings indicate the important role of depression (e.g., D4) and stress (e.g., S4) issues in the comorbidity network of specific types of PIU and psychological distress symptoms. The symptom 'down-heartedness' was assessed using the item *I felt down-hearted and blue* from the DASS-21. Although not explicitly labeled in the DSM-5, this symptom is included as a diagnostic criterion for depression in many widely used clinical screening tools, such as the Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977) and the Hospital Anxiety and Depression Scale (HADS; Zigmond & Snaith, 1983). The clinical significance of this symptom suggests that mental health professionals should pay attention to individuals' down-hearted feelings or expressions associated with their specific PIU. Theories and empirical studies have identified the relationship between PIU and poor mental health (Brand et al., 2019; Hussain et al., 2020; Lopes et al., 2022). The present study deepens the understanding of such relationship at symptom level, which might be helpful for potential preventions to target more specific symptoms.

Wang et al. (2022) found that the depression symptom of 'lack of enthusiasm' was the central symptom in the comorbidity network of PSMU, anxiety, and depression. They asserted that depression plays an important role in influencing an individual's PSMU. Similarly, the present study also identified that depression (*down-hearted*) and stress ('agitated') symptoms are the central symptoms over time. This again suggests that psychological distress symptoms are the core problems in the comorbidity mechanism of specific types of PIU and poor mental health.

However, different from the present study, a cross-sectional study by Cai et al. (2021) reported that the most central symptoms in the PIU-anxiety network were the PIU symptoms such as 'affected academic performance', 'social conflict', and 'mood modification'. Tullett-Prado et al. (2023) also found that the PSMU symptoms 'tolerance' and 'mood-modification' were the most central symptoms in the PSMU- psychological distress network models over time. Such different results might be attributed to variations in node representations (e.g., specific symptoms versus total scores) or differences in the social-demographic backgrounds of the samples. Future studies could explore the specific PIU-psychological distress network across different age groups or cultural contexts, analyzing both symptom-level and total score-level interactions.

Another longitudinal network analysis study indicated that both PIU symptoms ('escape' and 'irritability') and depression symptoms ('low energy' and 'guilt') were the most central or most connected symptoms within the PIU-depression comorbidity network over time (Zhao et al., 2023). However, it should be noted that these studies examined different types of PIU, such as generalized PIU (Cai et al., 2021; Zhao et al., 2023) and PSMU (Tullett-Prado et al., 2023; Wang et al., 2022), which could lead to different results. Additionally, some did not focus on specific symptoms of anxiety or depression but used the total scores (e.g., DASS-21; Tullett-Prado et al., 2023), which might not allow for the detection of potential central symptoms in the psychological distress variables. Therefore, the central symptoms in the PIU-psychological distress comorbidity network could be different depending on the research focus and data analysis approaches.

In terms of bridging symptoms, the present study found that the PSMU symptoms of 'mood modification' and 'conflict/functional impairment' were key bridging nodes that connect specific PIU and psychological distress symptoms, especially in T1 and T2. Similarly, Wang et al. (2022) also found that the symptom 'conflict/functional impairment' in PSMU was the key linking node with highest betweenness in the network of PSMU, anxiety, and depression. Based on these findings, it appears that 'conflict/functional impairment' is the key symptom that played an important role linking or mediating the symptoms between the two communities of specific PIU and

psychological distress. This indicates that many symptoms between specific PIU and psychological distress may be connected through 'conflict/functional impairment' in PSMU. Such findings support the inclusion of the term 'functional impairment' within the concepts of PSMU and PIU (Billieux et al., 2017). On the other hand, the present study found that bridging symptoms might change over time, and that the depression symptom 'no initiative' (D2) became the key bridging symptom in T3. Zhao et al. (2023) reported that the key bridging symptoms in the PIU-depression network were 'guilty' (*Feeling bad about yourself, or that you are a failure or have let yourself or your family down*) in depression and 'escape' in PIU over time. Therefore, either the specific PIU or psychological distress symptoms could be the key connecting node in different stages of the development of the comorbidity. Consequently, it is important to further explore the change of bridging symptoms over time with longitudinal designs.

The CLPN analysis in the present study showed that PIU symptoms were the most influential and susceptible symptoms from T1 to T2, while psychological symptoms become the dominant symptoms from T2 to T3. In the interval between T1 and T2, the PSMU symptom 'conflict/functional impairment' had the highest Out-EI, making it the most influential symptom that predicted the other symptoms subsequently. 'Salience' and 'withdrawal' in PSMU had the highest In-EI values, making them the most susceptible symptoms predicted by the other symptoms in earlier waves. This shows that PIU symptoms, especially those related to PSMU, were the key drivers that contribute to the development of the comorbidity network of PIU and psychological distress symptoms.

Such findings are similar to previous longitudinal studies using the CLPN approach, which identified that the PIU symptoms 'time management' and 'tolerance' were the most influential in the comorbidity network over time (Jia et al., 2024; Qu et al., 2024). Therefore, antecedent PIU symptoms might serve as the initial starting point in the comorbidity mechanism, which contributes to subsequent mental health risks. Moreover, the present study's findings indicated that PSMU symptoms were the most susceptible symptoms from T1 to T2. This finding suggests a potential bidirectional relationship between PIU and psychological distress, as supported by earlier longitudinal studies (e.g., Marttila et al., 2021; Teng et al., 2021; W. Zhou et al., 2023). It is therefore important to focus on the problems associated with PIU, particularly the symptoms of 'conflict/functional impairment' and 'tolerance', when implementing prevention measures for psychological distress related to internet use. Moreover, the present study's findings also indicated that PSMU symptoms (more than POVW symptoms) appear to play more important roles in the comorbidity.

Interestingly, the present study's three waves of surveys identified that the influential and susceptible symptoms can change over time. Unlike the first interval (from T1 to T2), psychological distress symptoms (especially depression symptoms) were the most influential and susceptible from T2 to T3. In four waves of studies conducted from 2011 and 2012, Jia et al. (2024) reported that PIU symptoms were consistently the most influential ones in the network, and depression symptoms were consistently the most susceptible ones over time. The different results might be due to the length of intervals, the year of data collection and/or measurement instrument used to assess PIU. Nevertheless, the present study observed a shift in key influential and susceptible symptoms (from PIU to psychological distress), indicating that the comorbidity network can change over time. This suggests that mental health problems might become the primary drivers of PIU symptoms and outcomes of PIU in later stages of the comorbidity's development.

Moreover, the impact of the COVID-19 pandemic should be considered when comparing the present study with Jia et al. (2024)'s study, which used data from over 10 years ago. The present study collected data during the COVID-19 pandemic, a period when participants' psychological distress may have been influenced by pandemic-related stressors. The pandemic likely accelerated the adoption of digital technologies for essential activities, such as online learning. This shift may have contributed to increased screen time and reliance on the internet, potentially exacerbating specific PIU behaviors. However, Jia et al. (2024) collected data from 2011 to 2014, a timeframe that predates the pandemic. It is also unclear how environmental factors influenced their results during those four years.

From the perspectives of specific symptoms and longitudinal development, the present study contributes to the understanding of the bidirectional relationship between PIU and psychological distress, as proposed in some theoretical frameworks (e.g., Brand et al., 2019; Sonuga-Barke et al., 2024). Specific symptoms of PSMU, particularly 'conflict/functional impairment', play a significant role in the comorbidity of PIU and psychological distress. Furthermore, the key predictors and outcomes in this comorbidity mechanism might change over time because psychological distress could become the dominant variable in later stages. Such findings might further support the I-PACE theory, which proposed that compensation may become stronger over gratification in the later

stages of the development of addictive behaviors (Brand et al., 2016, 2019). In later stages of comorbidity, the compensatory effect may become stronger due to psychological distress, which could contribute to the cycle of PIU and further distress.

The findings suggest several intervention and prevention strategies for addressing specific PIU and psychological distress. Given that 'down-heartedness' (a depressive symptom) and 'agitation' (an anxiety symptom) emerged as central nodes in the comorbidity network, interventions such as cognitive-behavioral therapy (CBT) should prioritize mitigating these symptoms to disrupt the broader interplay between distress and PIU. Additionally, the bridging role of the PSMU symptoms 'mood modification' and 'conflict/functional impairment' indicates the need to first address functional impairment associated with social media use (e.g., implementing time-management tools for social media engagement). Moreover, stage-specific approaches could enhance intervention efficacy. In early stages (where PSMU symptoms drive comorbidity), screening for symptoms such as 'mood modification' during the first term of being undergraduate students may help identify at-risk individuals. In later stages (where depressive symptoms dominate), interventions should prioritize treating depressive symptoms to disrupt the self-reinforcing cycle within the comorbidity.

Limitations and Future Directions

There are a number of limitations in the present study. The self-reported scores for specific PIU and psychological distress variables may be biased due to social desirability and memory recall. The present study did not include attention-check questions in the survey, which may be a limitation. The predictive relationships identified in the present study may not illustrate cognitive neural mechanisms underlying specific PIU and psychological distress. Future studies could employ experimental designs (e.g., event-related potential studies) to explore this further. Moreover, the cross-lagged methods might not establish causation, even though the findings suggest bidirectional temporal links between specific types of PIU and psychological distress. Future studies need to focus on the confounders not examined in the present study (e.g., personality traits, life stressors) that may contribute to the observed associations.

Moreover, the present study's recruitment of university students may limit the generalizability of the results. Further studies could recruit more diverse samples with varying demographic characteristics, such as different ages or cultural backgrounds. The sample exhibited a gender imbalance, with females comprising 67.7% of all participants. This imbalance may limit the generalizability of the findings. Future studies should conduct studies with more balanced gender samples and explore gender-moderation effects. Moreover, the present study did not assess participants' experience with or frequency of social media use and online video consumption. The assumption that all participants engaged in these activities is a potential limitation.

Another limitation might be the impact of the COVID-19 pandemic. Data collection occurred between 2021 and 2022, coinciding with pandemic-related public health measures including lockdowns, social distancing, and remote learning/work arrangements. While these contextual factors may have moderated relationships between specific PIU and mental health, it should be noted that the three survey waves neither captured the pandemic's initial phase nor its resolution period.

Only two specific PIU types were included in the present study. Therefore, future studies test additional PIU subtypes and mental health outcomes using longitudinal network analysis. Finally, the present study only included depression, anxiety, and stress as the psychological distress variables, which might ignore the other potential mental health risks. Future studies could include additional types of psychological factors or disorders such as low self-esteem, obsessive-compulsive disorder, and bipolar disorder.

Conclusion

The present study found that the psychological distress symptoms ('down-heartedness' and 'agitation') were consistently the most central symptoms in the PIU-psychological distress comorbidity network. The PSMU symptoms of 'mood modification' and 'conflict/functional impairment' were consistently the key bridging symptoms between the other symptoms. The CLPN analysis showed that the comorbidity mechanism of specific PIU and psychological distress can change over time. In earlier stages, PSMU symptoms may be the main predictors and outcomes in this seemingly bidirectional relationship. In later stages, psychological distress symptoms, especially depressive symptoms, become the most influential and susceptible symptoms. The present

study explored the comorbidity of specific PIU and psychological distress, identifying the dynamic development of this bidirectional relationship over time at the symptom level. Preventions could target central psychological distress symptoms and bridging PSMU symptoms through stage-specific approaches.

Conflict of Interest

The authors have no conflicts of interest to declare.

Use Of AI Services

The authors declare they have not used any AI services to generate or edit any part of the manuscript or data.

Authors' Contribution

Wenting Xu: conceptualization, data curation, formal analysis, investigation, methodology, software, visualization, writing—original draft, writing—review & editing. **Zeyang Yang:** conceptualization, data curation, formal analysis, funding acquisition, methodology, project administration, resources, supervision, validation, writing—original draft, writing—review & editing. **Zhihao Yan:** conceptualization, data curation, formal analysis, investigation, writing—original draft, writing—review & editing. **Yuanli Liu:** writing—original draft, writing—review & editing. **Mark D. Griffiths:** writing—original draft, writing—review & editing.

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Ethics

This study has been approved by the Ethics Committee of the School of Education at Soochow University.

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