MUNI FSS

JOURNAL OF PSYCHOSOCIAL RESEARCH ON CYBERSPACE
CYBERPSYCHOLOGY

Liu, Y., & Yang, Z. (2026). The dynamic interplay between cyberchondria and health anxiety in online health information seeking: A four-wave longitudinal network analysis. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace, 20*(5), Article 1. https://doi.org/10.5817/CP2026-5-1

The Dynamic Interplay between Cyberchondria and Health Anxiety in Online Health Information Seeking: A Four-Wave Longitudinal Network Analysis

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Abstract

As online health information seeking becomes increasingly common, cyberchondria has emerged as a concern associated with people's maladaptive health perceptions and quality of life. However, the longitudinal interplay between cyberchondria and related psychological factors remains unclear. This study used cross-lagged panel network analysis (CLPN) to examine the relationships between cyberchondria, health anxiety, problematic social media use (PSMU), security, health self-efficacy, and life satisfaction across four waves of longitudinal data from 722 participants. The initial three surveys were conducted at one-month intervals, with the final survey conducted six months later. Cyberchondria and health self-efficacy were the most influential nodes across multiple networks. Throughout all transition periods, bidirectional longitudinal predictive pathways exist between cyberchondria and health anxiety. Life satisfaction and security demonstrated notable influence in the network. Using a data-driven approach, the present study highlights a dynamic reinforcement pattern between cyberchondria and its correlates. Future research could further explore these pathways to provide new insights into the mechanisms of cyberchondria.

Keywords: cyberchondria; health anxiety; health self-efficacy; life satisfaction; problematic social media use; security

Editorial Record

First submission received:
March 11, 2026

Revisions received:
July 9, 2026
September 29, 2026

Accepted for publication:
October 2, 2026

Editor in charge:
Maèva Flayelle

Introduction

The growing volume of online health information has changed how individuals deal with health-related uncertainty. Unlike offline reassurance-seeking with others, digital environments provide immediate, often algorithmically amplified exposure to information. In this context, cyberchondria may not just involve excessive searching but also represents a dynamic psychological process in which health-related concerns are constantly reinforced (Starcevic et al., 2021). Understanding how this process evolves over time is essential for advancing digital mental health research. The term "cyberchondria", a portmanteau of "cyber" and "hypochondriasis", traces its origins to a 1990s media report highlighting the dark side of digital health (Vismara et al., 2020). Cyberchondria has been described as a "devastating obsession", reflecting a silent yet pervasive mental health crisis within the digital environment (Köhler, as cited in Starcevic & Berle, 2013, p. 205). Cyberchondria primarily refers to the repetitive or excessive search for online health information accompanied by heightened emotional distress or amplified anxiety (Starcevic, 2017). Unlike traditional hypochondriasis, individuals seek to alleviate health anxiety

through online searches but often become trapped in a vicious cycle of information overload, unease, and fear (Salkovskis et al., 2003). McElroy et al. (2019) describe cyberchondria as a multifaceted concept with two aspects: it appears as excessive searching for health information online driven by anxiety and as increased psychological distress caused by losing control over this behaviour. Although many scholars have interpreted definitions of cyberchondria from different perspectives, the academic community has yet to reach a consensus on its exact definition (Mestre-Bach & Potenza, 2023; Starcevic, 2017).

The Cognitive-Behavioural Model of the Development and Persistence of Health Anxiety (Hypochondriasis; Salkovskis et al., 2003) suggests that hypochondriasis might arise from individuals' misinterpretations of bodily symptoms and other health information as signs of serious illness. Such biased beliefs can increase health anxiety and lead to more repetitive safety-seeking behaviours for reassurance. The health anxiety and excessive searching behaviours can form a vicious loop. This model shows the interaction among cognitive bias, arousal, health anxiety, and safety-seeking, providing a helpful framework for explaining the correlates of cyberchondria. Similarly, the Model of Cyberchondria during the COVID-19 pandemic also proposes a reciprocal loop between perceptions of threat, coping with uncertainty, excessive searching, and distress (Starcevic et al., 2021).

Health anxiety is one of the most important risk factors of cyberchondria (Bajcar & Babiak, 2021; Ciułkowicz et al., 2022; McMullan et al., 2019; Mestre-Bach & Potenza, 2023; Vismara et al., 2020). Some studies suggest that health anxiety leads to cyberchondria, proposing that the latter is an online search behaviour people use to reduce anxiety, even though it often has counterproductive effects (Baumgartner & Hartmann, 2011; White & Horvitz, 2009). Some other studies indicate that even without explicit health anxiety, individuals may engage in cyberchondria driven by other motives, such as curiosity and seeking information (Singh et al., 2016; Te Poel et al., 2016). Information seeking can increase health anxiety levels (Te Poel et al., 2016). Thus, a bidirectional relationship may exist between cyberchondria and health anxiety (Menon et al., 2020; Starcevic & Berle, 2013). To further explore the reciprocal rather than unidirectional relationship, longitudinal designs with repeated measurements might be suitable.

Problematic social media use (PSMU) is another key issue related to cyberchondria (Ahorsu et al., 2022). PSMU refers to the uncontrollable and compulsive use of social media, resulting in functional impairment (Andreassen & Pallesen, 2014). Compulsive seeking of reassurance is a key characteristic of cyberchondria, which has now been identified as a cross-diagnostic obsessive-compulsive syndrome type associated with problematic internet use (Vismara et al., 2020). Multiple studies show that students' dependence on social media for health information significantly worsens cyberchondria, a phenomenon closely associated with smartphone addiction and a low tolerance for uncertainty (Bahadir & Dundar, 2024; El-Zoghby et al., 2024). Türk Kurtça (2025) found that cyberchondria significantly and positively predicted PSMU. Individuals who more frequently and compulsively searched for health information online and consequently experienced anxiety were more likely to develop PSMU. Meanwhile, Ahorsu et al. (2022) proposed that PSMU directly and positively predicted cyberchondria, meaning higher levels of PSMU correlated with higher levels of cyberchondria.

Beyond risk factors, cyberchondria can be linked to positive psychological factors, including perceived security, health self-efficacy, and life satisfaction. Security, in this context, acts as a stabilising force that allows individuals to perceive risks without undue anxiety (Wei et al., 2023). Individuals with low security tended to catastrophise neutral physical sensations. This misinterpretation creates a feedback loop in which insecurity and cyberchondria increase (Jungmann & Witthöft, 2020; Singh & Brown, 2014). On the one hand, individuals with lower security may attempt to reduce uncertainty and anxiety through compulsive information seeking (Vismara et al., 2020; Starcevic et al., 2019). On the other hand, cyberchondria could increase psychological insecurity (social insecurity and uncertainty), which can, in turn, predict mental health risks (Liu et al., 2023). The anxiety-reassurance and insecurity-cyberchondria loops appear to both unfold over time. However, most supporting evidence remains cross-sectional. It is unclear whether they can be reproduced across successive occasions. Therefore, a multi-wave design is needed to explore the bidirectional links over time. Four waves serve this end, since the two one-month transitions act as a within-study replication while the six-month transition indicates whether the same links persist as health concerns recede.

Health self-efficacy extends the self-efficacy concept to health, referring to an individual's confidence in executing and maintaining health-promoting behaviours to achieve health outcomes (Lee et al., 2008). Notably, diminished health self-efficacy raises individuals' likelihood of experiencing more negative emotional states and a greater disease burden (Finney Rutten et al., 2016; Merluzzi & Martinez Sanchez, 1997). Individuals with higher self-efficacy exhibit stronger motivation and more frequent engagement in online health information searches (Tang & Lee,

2006). It was found that health self-efficacy, information credibility, and information overload collectively contribute to the development of cyberchondria (Gu & Chen, 2023). Higher levels of health self-efficacy among older adults are associated with a greater likelihood of developing cyberchondria (Gu et al.,2025). However, the relationship between the two remains unclear. Studies have demonstrated a negative association between self-efficacy and problematic online behaviours (POBs), such as problematic online gaming and short-video addiction (Arslan, 2022; Yang, 2020; Zhao & Kou, 2024). Given that cyberchondria has been recognised as a type of POBs (Baggio et al., 2022), further research is needed to clarify the specific relationship between health self-efficacy and cyberchondria.

Life satisfaction is another potential correlate of cyberchondria, as previous studies have identified weak, negative correlations between the two (Tunç et al., 2023; Mathes et al., 2018). Individuals with low life satisfaction reported higher problematic internet use (Lachmann et al., 2016; Capa-Luque et al., 2025) and higher sensitivity and intolerance toward life uncertainties (Seçer & Sevinç Yılmaz, 2025). To alleviate this uncertainty, they engage in repetitive and compulsive online health searches, which exacerbates cyberchondria (Vujić et al., 2023). Given that health anxiety negatively predicted life satisfaction (Pepe et al., 2025) and the close relationship between health anxiety and cyberchondria, as noted above (Bajcar & Babiak, 2021; Nadeem et al., 2022), it is necessary to further explore this association.

Taken together, the variables noted above could represent three main theoretical domains of the development of cyberchondria, including (1) the classic health anxiety relieving loop, (2) the related problematic online behaviours, and (3) psychological resources. The core link between cyberchondria and health anxiety represent the loop of anxiety reassurance and repetitive health information seeking as described in the cognitive-behavioural models of health anxiety (Salkovskis et al., 2003; Starcevic et al., 2021). PSMU represents the problematic or excessive online behavioural involvement related to cyberchondria. Security, health self-efficacy, and life satisfaction represent the psychological resources that may influence individuals' coping with health anxiety or sense of uncertainty. Therefore, it is necessary to explore the links between cyberchondria and the potential related factors in a broader system, including anxiety, online behaviour, and psychological resources.

To date, several studies have employed network analysis as a data-driven approach to investigate cyberchondria. Starcevic et al. (2019) published the first network analysis article on cyberchondria and found that cyberchondria constitutes a distinct construct, with problematic internet use and health anxiety exhibiting the strongest associations. Subsequent network analysis studies have confirmed cyberchondria as a subtype of problematic online behaviours (POBs; Baggio et al.,2022) and identified its close association with PSMU (Pezzi et al.,2024), problematic online shopping (Błoch & Misiak,2025), and pandemic fear (Li et al.,2024). A recent two-wave longitudinal network study shows that cyberchondria was predicted by earlier PSMU and predicted higher subsequent loneliness (Błoch & Misiak, 2026). It is important to note that most existing studies employed cross-sectional data to construct network models, which were unable to examine the longitudinal dynamics among these variables.

Although previous studies have examined the relationships between cyberchondria and both positive and negative correlates, most have been limited to cross-sectional designs and hypothesis-testing approaches. Therefore, this study adopts longitudinal network analysis, a data-driven approach, utilising four waves of longitudinal data to construct dynamic psychological network models. Cross-Lagged Panel Network Analysis (CLPN) models were estimated to detect the longitudinal predictive relationships between cyberchondria, health anxiety, PSMU, security, health self-efficacy, and life satisfaction. The central variables at four time points and the key predictive paths over time were identified. Although previous studies have suggested the relationships between cyberchondria and health anxiety, PSMU, and psychological resources, evidence on the longitudinal network involving these variables is limited. Therefore, rather than propose confirmatory hypotheses, the present study adopted research questions and used data-driven CLPN analysis. The research questions are as follows:

RQ1: Which variables are most central in the networks of cyberchondria and its correlates across the four waves?

RQ2: Which variables are the strongest predictors (higher Out-EI) and the most susceptible to prediction (higher In-EI) in the cross-lagged panel networks?

RQ3: Which cross-lagged paths involving cyberchondria are consistently retained across the transition periods?

Methods

Participants and Procedures

The participants were recruited through the Credamo online survey platform. All participants completed the questionnaire after providing informed consent and were informed of the study's anonymity and data confidentiality measures. The inclusion criteria were: (1) being at least 18 years old, (2) being able to read Chinese, and (3) providing informed consent. Participants were excluded if they failed to answer the two attention check questions correctly or selected the same option for all questions. The extreme responses were identified through calculating the standard deviation of the participants' responses across all items. Participants with an item-level SD of zero were identified as straight-line responses and excluded. Because the online survey platform required participants to answer all items before submitting their responses, no item-level missing values were observed. Demographic information was also collected. The survey was conducted from January to September 2025 (T1 = 1,161; T2 = 1,105; T3 = 1,042; T4 = 722). Participants received phased compensation based on the number of surveys completed, with a maximum of 20 CNY. The retention rates were 95.18% from T1 to T2, 94.30% from T2 to T3, and 69.29% from T3 to T4. The overall retention rate from T1 to T4 was 62.19% (722/1,161). The final analytic sample comprised 722 participants (males = 293; females = 429) who completed all four waves and had valid data on all variables. This study was approved by the Ethics Committee of the authors' university (reference number: A115010222) and strictly adhered to the ethical principles outlined in the Declaration of Helsinki.

No priori power analysis was conducted for the sample size of the CLPN analysis before data collection because there is no widely accepted approach for calculating sample size for LASSO-regularised CLPN models. We evaluated the adequacy of our sample for cross-sectional network estimation using the "netSimulator()" function in the bootnet package as suggested by Epskamp and Fried (2018). Using the refitted T1 network as reference, simulations (100 replications per sample size) showed that at N = 722, the correlation between the "true" and estimated networks was above 0.8 for edge weights (r = .99) and strength (r = .98), and sensitivity was above 0.7 (sensitivity = .92). At N = 1,000, these values were r = .99, r = .99, and sensitivity = .95, respectively. These results show that the sample size was adequate for cross-sectional network analysis.

Considering that cyberchondria is a rapidly evolving short-term phenomenon, individuals' cyberchondria levels may decline rapidly when perceived health threats diminish or disappear. Therefore, for the first three surveys, we set a one-month interval as suggested in previous studies (Song & Min, 2024; Zheng et al., 2022). However, short-interval designs may not indicate whether the links between cyberchondria and its correlates remain observable over longer periods. Longer intervals, particularly six-month intervals, provide sufficient time for sustained health-related online behaviours to recur while maintaining the study manageable for participants. Such intervals are widely adopted in longitudinal studies of problematic online behaviours, including cyberchondria (e.g., Błoch & Misiak, 2026). Therefore, a fourth wave was administered six months after Wave 3 to extend the temporal scope of the present study and to estimate CLPN for a longer transition period. Since the path coefficients across different time intervals might not be directly comparable, the present study did not intend to compare the paths between intervals. CLPN models were estimated separately for each transition period, and cross-lagged coefficients were interpreted within the transition period only.

Measures

Cyberchondria

The Short Cyberchondria Scale (SCS; Jokić-Begić et al., 2019) was employed to assess participants' levels of cyberchondria. The Chinese version of this scale has been thoroughly validated within the Chinese cultural context (Zheng et al., 2023). The scale comprises four measurement items designed to capture the characteristics of cyberchondria across two core dimensions: emotional and behavioural. All items employ a five-point Likert scale, with responses ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). Higher total scores indicate more severe tendencies toward cyberchondria. In this study, cyberchondria demonstrated good internal consistency (Cronbach's α: T1 = .859, T2 = .857, T3 = .870, T4 = .856).

Health Anxiety

The Whitley Index-6 (WI-6; Asmundson et al., 2008) scale was used to assess participants' levels of health anxiety. The Chinese version of this scale has been fully validated within the Chinese cultural context (Zheng et al., 2022). The scale comprises six items scored on a five-point Likert scale ranging from 1 (*Strongly disagree*) to 5 (*Strongly agree*). Higher scores indicate more severe health anxiety. In this study, health anxiety demonstrated good internal consistency (Cronbach's α: T1 = .895, T2 = .888, T3 = .894, T4 = .895).

PSMU

The Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2017) was used to assess participants' PSMU levels using six items. The Chinese version of this scale has been thoroughly validated within the Chinese cultural context (Hou et al., 2019). A 5-point Likert scale was used (1 = *Never*, 5 = *Always*). Each item describes a dimension of addictive behaviour: salience, emotional regulation, tolerance, withdrawal symptoms, conflict, and relapse. Higher scores indicate greater PSMU. In this study, the PSMU demonstrated good internal consistency (Cronbach's α: T1 = .822, T2 = .828, T3 = .830, T4 = .817).

Security

The Psychological Safety Scale (SQ; Cong & An, 2004) was used to measure participants' security levels. This scale has been thoroughly validated in previous research (Liu et al., 2023). The scale comprises 16 items across two dimensions: interpersonal security and sense of control. It employs a 5-point Likert scale (1 = *Strongly agree*, 5 = *Strongly disagree*). Higher scores indicate greater psychological security. In this study, the scale demonstrated good internal consistency (Cronbach's α: T1 = .935, T2 = .941, T3 = .933, T4 = .935).

Health Self-Efficacy

Health self-efficacy was assessed using the five-item scale developed by Lee et al. (2008). The Chinese version of this scale has been fully validated within the Chinese cultural context (Wang et al., 2021). The scale employed a 5-point Likert scale (1 = *Strongly disagree*, 5 = *Strongly agree*). Higher scores indicated greater health self-efficacy. In this study, health self-efficacy demonstrated good internal consistency (Cronbach's α: T1 = .800, T2 = .796, T3 = .768, T4 = .757).

Life Satisfaction

The Satisfaction With Life Scale (SWLS; Diener et al., 1985) was used to assess individuals' overall life satisfaction. The Chinese version of this scale has been thoroughly validated within the Chinese cultural context (Bai et al., 2011). The scale comprises five items scored on a 7-point Likert scale (1 = *Very dissatisfied*, 7 = *Very satisfied*). Higher scores indicate greater life satisfaction. In this study, life satisfaction demonstrated good internal consistency (Cronbach's α: T1 = .895, T2 = .919, T3 = .912, T4 = .924).

Data Analysis

CLPN has seen widespread application in psychological, sociological, and medical research in recent years (Jiang et al., 2025; Misiak, 2025; Zhang et al., 2025). This method integrates a cross-lagged panel design with network analysis, enabling identification of key paths from earlier symptoms to subsequent symptoms within the network over time (Granero et al., 2021). ExpectedInfluence (EI) shows the node centrality, where out expected influence (Out-EI) reflects a node's potential to actively influence other nodes, while in expected influence (In-EI) indicates its susceptibility to being influenced by others (Funkhouser et al., 2021; Robinaugh et al., 2016; Wysocki et al., 2022).

All analyses were conducted using R (Version 4.5.1). Based on longitudinal data from four time points, this study constructed cross-sectional and cross-lagged networks for all variables. Model selection employed the Graphical Minimum Absolute Shrinkage and Selection Operator with Extended Bayesian Information Criterion (EBICglasso), and these networks were visualised using the qgraph package. Node importance was assessed through

ExpectedInfluence (EI; Epskamp et al., 2018). The reliability of network structures was estimated using the Bootstrapping method to obtain confidence intervals for edge weights (Fried et al., 2018). The stability of centrality measures can be assessed using the stability coefficient (CS-coefficient), which is generally considered valid when above 0.5 and not below 0.25 (Epskamp et al., 2018). Three CLPN networks were estimated using the glmnet package, and In-EI and Out-EI were calculated. LASSO with 10-fold cross-validation tuning parameter selection was used to regularise the regression coefficients. Autoregressive paths were excluded from the final adjacency matrices by setting diagonal elements to zero. Thus, the CLPN networks focused on cross-lagged associations among different constructs. Because CLPN edges were estimated using LASSO regularisation, conventional p-values were not calculated. Non-zero coefficients indicate paths retained by the regularised model rather than statistically significant effects. Edge-weight accuracy was evaluated using bootstrapped confidence intervals, and edge stability was assessed using case-dropping bootstrap procedures. Network structure invariance across four time points was tested using the NetworkComparisonTest package. Network accuracy and stability were estimated using the bootnet package.

The total scores of the scales were used as CLPN nodes because the aim of the study was to explore construct-level longitudinal links between the variables. Although cyberchondria and health anxiety can be multidimensional constructs when longer scales are used, the short scales adopted in the present longitudinal study include a limited number of items and were unidimensional, as shown in the Confirmatory factor analyses (CFA) results. Therefore, the total scores were more suitable for the CLPN in this study.

Results

Descriptive Statistics and Correlation Analysis

Table 1 presents the demographic information of 722 participants. Among them, 40.6% were male and 59.4% were female. Their ages ranged from 18 to 65 years (M_{age} = 32.03; SD_{age} = 7.175). The majority of participants (68%) held a bachelor's degree, with a median annual income between “150,000 – 199,000 CNY”. Nearly half of the participants used electronic screens for more than 3 hours daily (41.7%) and reported their health status as “good” (42.4%). Table 2 indicates statistically significant correlations between health anxiety, PSMU, health self-efficacy, sense of security, life satisfaction, and cyberchondria at all time points (T1, T2, T3, and T4). Skewness and kurtosis values show that all variables were normally distributed. The CFA results indicated generally acceptable model fit across all scales across the four waves (see Appendix A1). These findings supported the use of total scores as construct-level indicators in the present study.

Attrition Analyses

Attrition analyses were conducted to compare the scores of the four-wave completers and those who dropped out before T4. The dropouts reported significantly higher cyberchondria ($t(953) = -3.79$, $p < .001$, $d = -.227$), health anxiety ($t(945) = -3.50$, $p < .001$, $d = -.211$), and PSMU ($t(900) = -2.79$, $p = .005$, $d = -.171$), as well as lower health self-efficacy ($t(956) = 2.46$, $p = .014$, $d = .147$), security ($t(907) = 4.33$, $p < .001$, $d = .264$), and life satisfaction ($t(936) = 2.11$, $p = .035$, $d = .127$) at baseline compared to completers. However, all observed effect sizes were small (|Cohen's d| range: .13–.26; Cohen, 1988). It suggests that while differences exist between completers and dropouts, the magnitude of these differences is small and unlikely to substantively bias the study's findings (e.g., Gustavson et al., 2012; Steinhausen et al., 2020).

Longitudinal Measurement Invariance

Longitudinal Measurement Invariance was tested using structural equation modelling. All six scales showed good model fit at the configural level (CFI = .941–.993, RMSEA = .035–.075, SRMR = .032–.069, see Appendix A2). Strict measurement invariance held for all six scales across the four time points (ΔCFI < .010, ΔRMSEA < .015, ΔSRMR < .030/.010; Chen, 2007). Thus, any score changes over time reflect true shifts in the constructs, not measurement drift. Full fit indices and model comparisons appear in Appendix A2.

Cross-Sectional Network Models

Network analysis was conducted to estimate the cross-sectional network structure of the variables from T1 to T4 (see Figure 1). There were six nodes in the network, representing the six variables: cyberchondria, health anxiety, health self-efficacy, PSMU, security, and life satisfaction. The number of non-zero edges was 15, 13, 14, and 13 (out of the total 15 edges) over time. The mean weights were 0.084, 0.080, 0.102, and 0.085, respectively. The links between cyberchondria and health anxiety were constantly the strongest over time. The network matrices are shown in Appendix A3.

Table 1. *Demographic Characteristics of the Sample.*

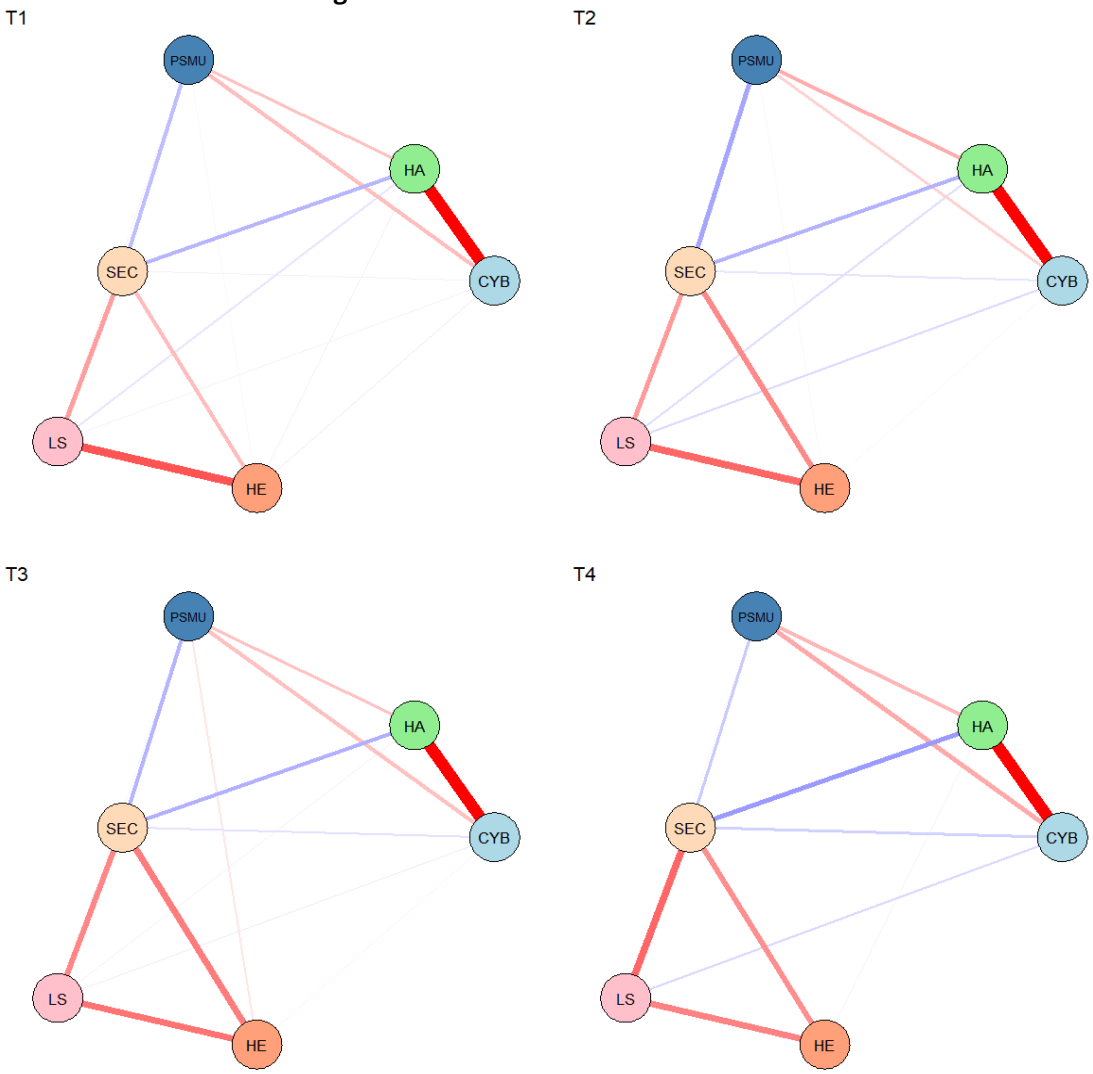
Variable	Category	Frequency	Percentage (%)
Age	18–30	302	41.8
	31–45	385	53.3
	46–60	33	4.6
	>60	2	0.2
Gender	Male	293	40.6
	Female	429	59.4
Education	Primary school	—	—
	Secondary school	1	0.1
	High school/Junior college	58	8.0
	Undergraduate	491	68.0
	Postgraduate and above	172	23.8
Income	Below 50,000 CNY	21	2.9
	50,000–99,999 CNY	81	11.2
	100,000–149,999 CNY	132	18.3
	150,000–199,000 CNY	134	18.6
	200,000–299,999 CNY	173	24.0
	300,000 CNY and above	181	25.1
Screen time	Below 10 min	1	0.1
	10–30 min	10	1.4
	30–60 min	51	7.1
	1–2 h	142	19.7
	2–3 h	217	30.1
	3 h and above	301	41.7
Health status	Poor	10	1.4
	Fair	126	17.5
	Good	306	42.4
	Very good	46	6.4
	Excellent	234	32.4

Table 2. *Descriptive Statistics and Pearson Correlation Analysis at T1-T4.*

	M	*SD*	Skewness	Kurtosis	Cyberchondria	Health anxiety	Health self-efficacy	PSMU	Security	Life satisfaction
T1										
Cyberchondria	11.19	4.23	0.18	−1.34	1					
Health anxiety	15.76	5.92	0.39	−1.12	.828**	1				
Health self-efficacy	20.03	3.21	−1.66	2.92	−.440**	−.460**	1			
PSMU	17.11	5.14	0.08	−0.87	.571**	.583**	−.360**	1		
Security	59.76	12.41	−1.06	0.41	−.544**	−.596**	.535**	−.497**	1	
Life satisfaction	21.93	6.26	−0.73	−0.40	−.461**	−.491**	.646**	−.386**	.579**	1
T2										
Cyberchondria	10.99	4.16	0.19	−1.35	1					
Health anxiety	15.38	5.71	0.43	−0.99	.806**	1				
Health self-efficacy	20.26	3.18	−1.79	3.46	−.415**	−.427**	1			
PSMU	17.09	5.13	0.09	−0.96	.542**	.583**	−.361**	1		
Security	60.06	12.89	−1.10	0.37	−.577**	−.625**	.599**	−.541**	1	
Life satisfaction	23.46	7.01	−0.70	−0.55	−.500**	−.519**	.619**	−.388**	.618**	1
T3										
Cyberchondria	11.04	4.29	0.22	−1.41	1					
Health anxiety	15.11	5.76	0.45	−1.06	.827**	1				
Health self-efficacy	20.57	2.95	−1.97	4.50	−.330**	−.383**	1			
PSMU	16.69	5.23	0.18	−0.99	.568**	.578**	−.259**	1		
Security	61.08	12.04	−1.09	0.39	−.589**	−.635**	.622**	−.517**	1	
Life satisfaction	23.89	6.85	−0.73	−0.46	−.451**	−.477**	.625**	−.371**	.664**	1
T4										
Cyberchondria	10.5	4.16	0.37	−1.25	1					
Health anxiety	14.75	5.76	0.60	−0.92	.806**	1				
Health self-efficacy	20.57	2.83	−1.87	3.74	−.393**	−.406**	1			
PSMU	16.53	5.07	0.23	−0.79	.577**	.574**	−.267**	1		
Security	61.28	12.22	−1.18	0.65	−.619**	−.651**	.571**	−.497**	1	
Life satisfaction	23.79	7.14	−0.76	−0.54	−.484**	−.462**	.561**	−.368**	.651**	1

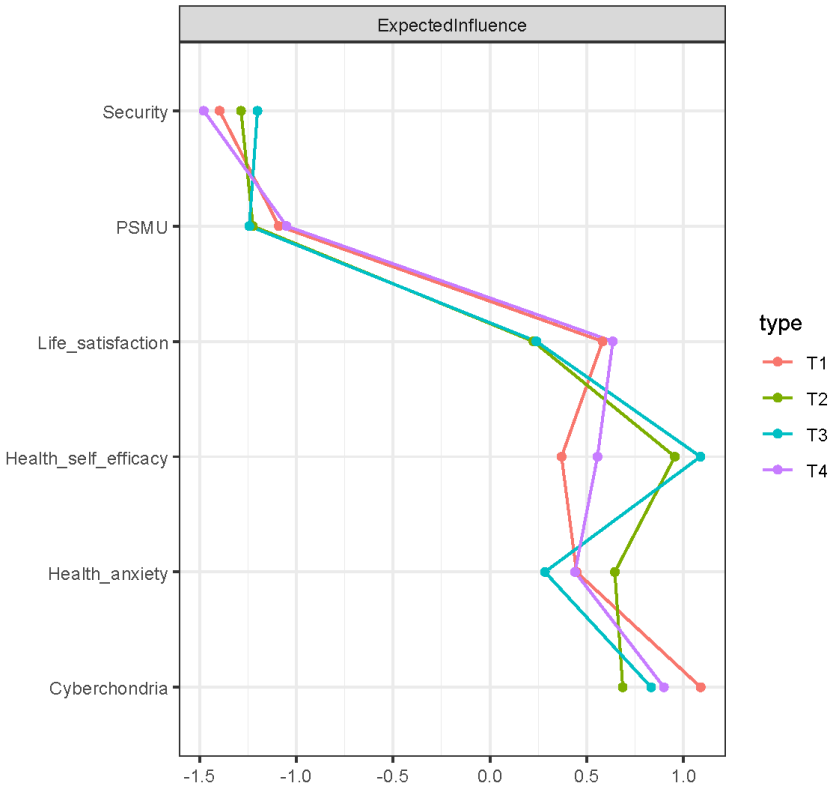
Note. *** for $p < .001$, ** for $p < .01$, and * for $p < .05$.

Figure 1. *Network Structures From T1 to T4.*



Note. Positive edges are in red, and negative edges are in blue. CYB: Cyberchondria; HA: Health anxiety; HE: Health self-efficacy; PSMU: Problematic social media use; SEC: security; LS: life satisfaction.

Figure 2. *Centrality Indices Values Over Time.*



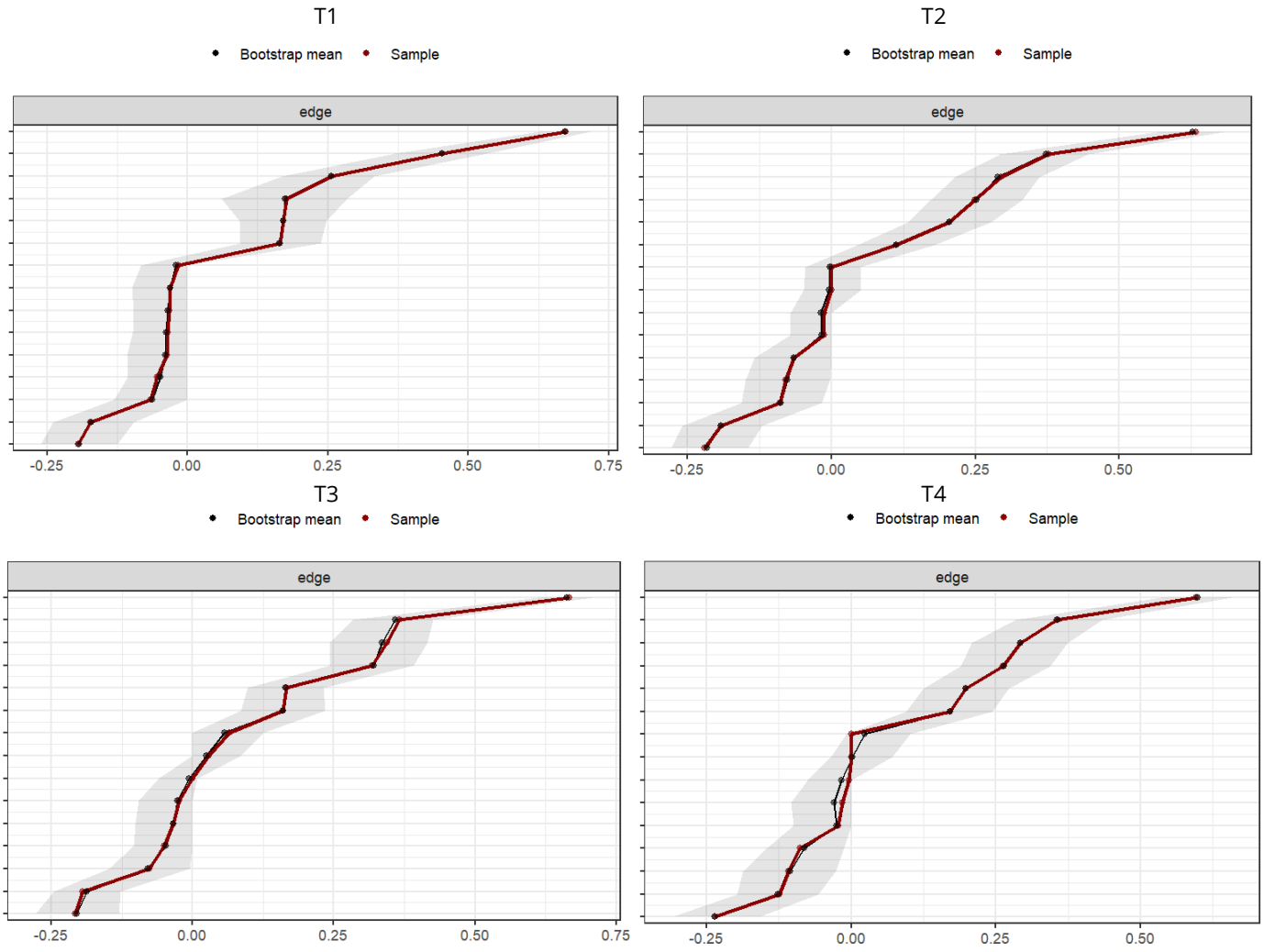
The centrality index, ExpectedInfluence, was estimated, as shown in Figure 2 and Table 3. The most influential nodes over time were: T1: cyberchondria (ExpectedInfluence = 1.089), T2: health self-efficacy (ExpectedInfluence = 0.955), T3: health self-efficacy (ExpectedInfluence = 1.087), T4: cyberchondria (ExpectedInfluence = 0.899).

Table 3. *ExpectedInfluence Over Time (Standardised).*

Variable	T1	T2	T3	T4
Cyberchondria	1.088798	0.685818	0.832659	0.898604
Health_anxiety	0.447117	0.645016	0.283921	0.439469
Health_self-efficacy	0.369668	0.955018	1.087385	0.55541
PSMU	−1.09062	−1.22404	−1.24287	−1.05036
Security	−1.39653	−1.28574	−1.20065	−1.47802
Life_satisfaction	0.581562	0.22393	0.239551	0.634899

The networks show good accuracy and stability. Figure 3 presents the estimated confidence intervals (CIs) of edge weights using non-parametric bootstrapping. The narrow CIs reflect good accuracy of the network model. The CS coefficients for ExpectedInfluence were 0.75, 0.75, 0.75, and 0.67 from T1 to T4, indicating good stability. The stability of centrality is demonstrated by the case dropping bootstrapping approach (see Fig. 4).

Figure 3. *Edge Weights and Bootstrapped Confidence Intervals.*

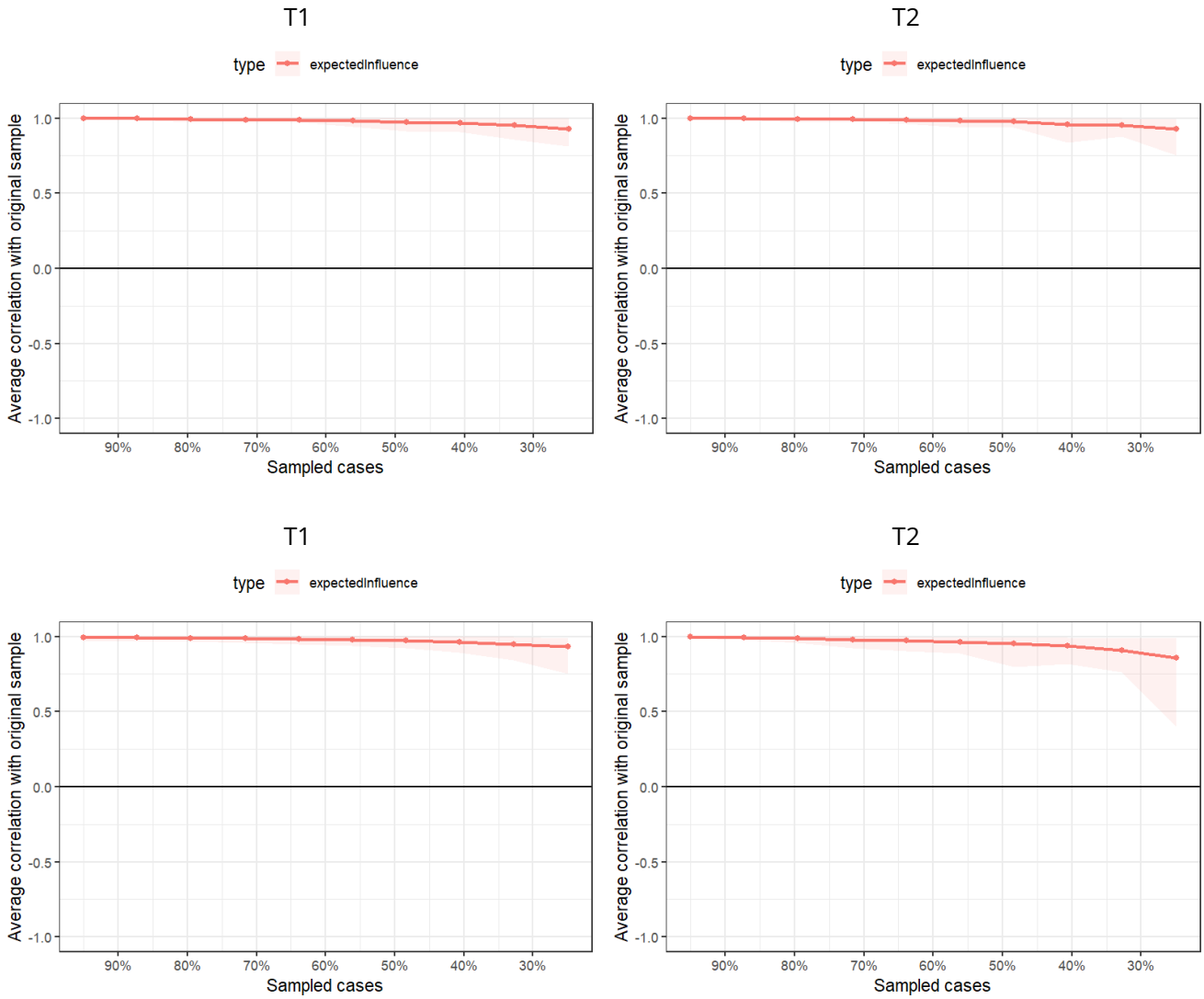


Note. The y-axis represents the edges. The red line represents the estimated edge, while the dark area indicates the 95% bootstrap confidence interval.

Network comparison tests were conducted between the networks at the four time points, and no difference was identified. Network invariance tests show that there was no significant network structure difference between T1

and T2 (Test statistic *M* = 0.12, *p* = .288, T2 and T3 (Test statistic *M* = 0.08, *p* = .714), and T3 and T4 (Test statistic *M* = 0.08, *p* = .719).

Figure 4. *Stability of ExpectedInfluence by Case Dropping Boot Strapping Approach.*



Note. The lines in the figure show the trend of the ExpectedInfluence correlation between subsamples and the original sample as the subsample sampling rate varies.

Node redundancy was assessed at each wave using the goldbricker function in the "networktools" package in R. Results show that cyberchondria and health anxiety were not identified as redundant at T1, T2, or T3. They were only flagged as suggested reductions at T4. In addition, life satisfaction and health self-efficacy were flagged at T1. It suggests that node redundancy was limited and the overlap between cyberchondria and health anxiety occurred only in the final wave.

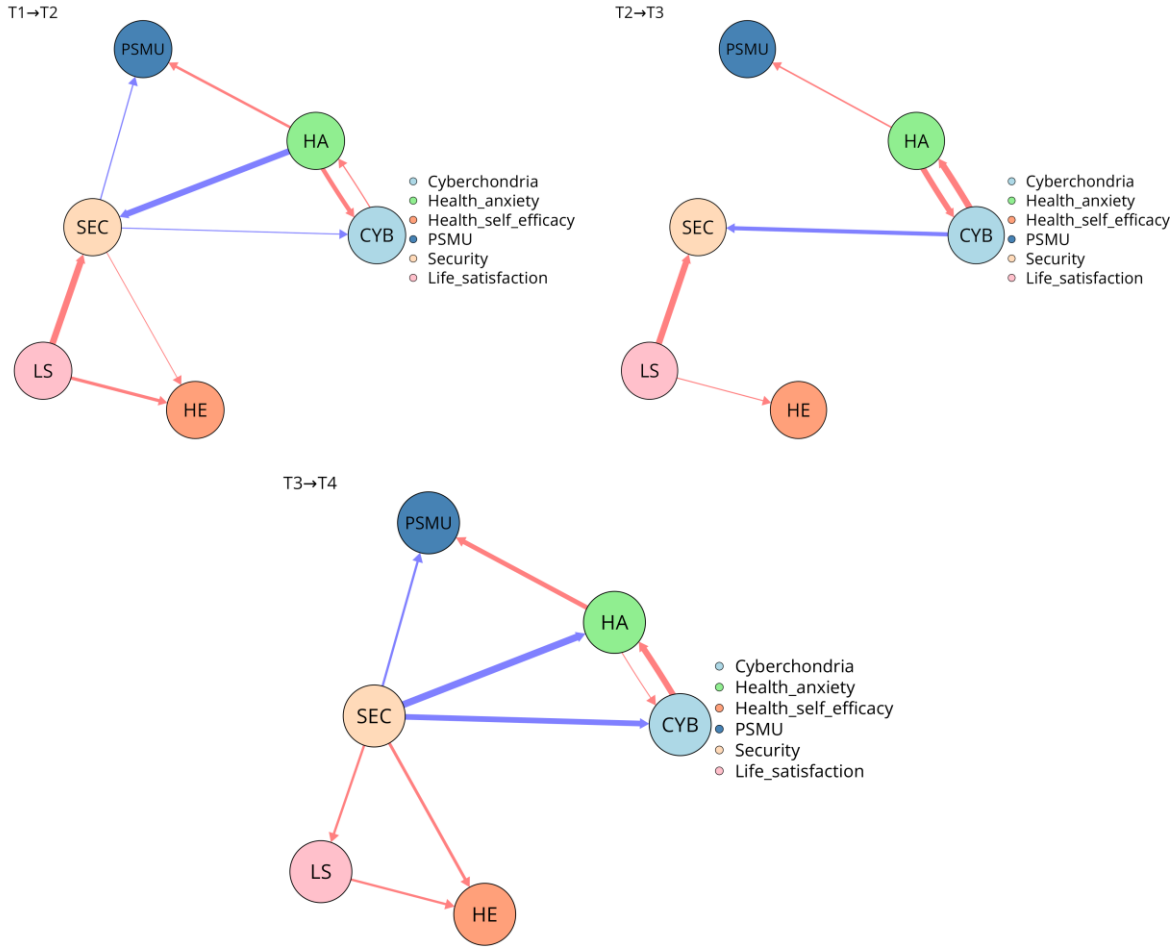
Gender differences were negligible across the six constructs at all four waves. Only health self-efficacy at T2 differed between men and women (males: *M* = 20.54, *SD* = 2.95; females: *M* = 20.07, *SD* = 3.31; *t*(671.0) = 2.00, *p* = .046), with a negligible effect size (Cohen's *d* = 0.15). All remaining comparisons had |d| ≤ 0.13 (see Appendix A7). Network structure also did not differ by gender. Network comparison tests showed no differences in network structure or global strength between the male and female subsamples at any wave (T1: test statistic [networkstructure] = 0.25, *p* = .052, test statistic S [global strength] = 0.10, *p* = .129; T2: test statistic *M* = 0.09, *p* = .876, test statistic S = 0.08, *p* = .176; T3: test statistic *M* = 0.12, *p* = .557, test statistic S = 0.12, *p* = .579; T4: test statistic *M* = 0.07, *p* = .987, test statistic S = 0.02, *p* = .831), and no individual edge differed at any wave.

Cross-Lagged Panel Network Analysis

CLPN were estimated across T1 to T2, T2 to T3, and T3 to T4 (see Figure 5). Red and blue paths represent positive and negative standardised regression coefficients. Thicker paths represent stronger relationships. Non-zero coefficients indicate predictive relationships retained after LASSO regularisation, while coefficients equal to zero

indicate that the corresponding effect was pruned. P-values are not provided in regularised models. The CLPN matrices were shown in Appendix A4.

Figure 5. *Cross-Lagged Panel Network Structures.*



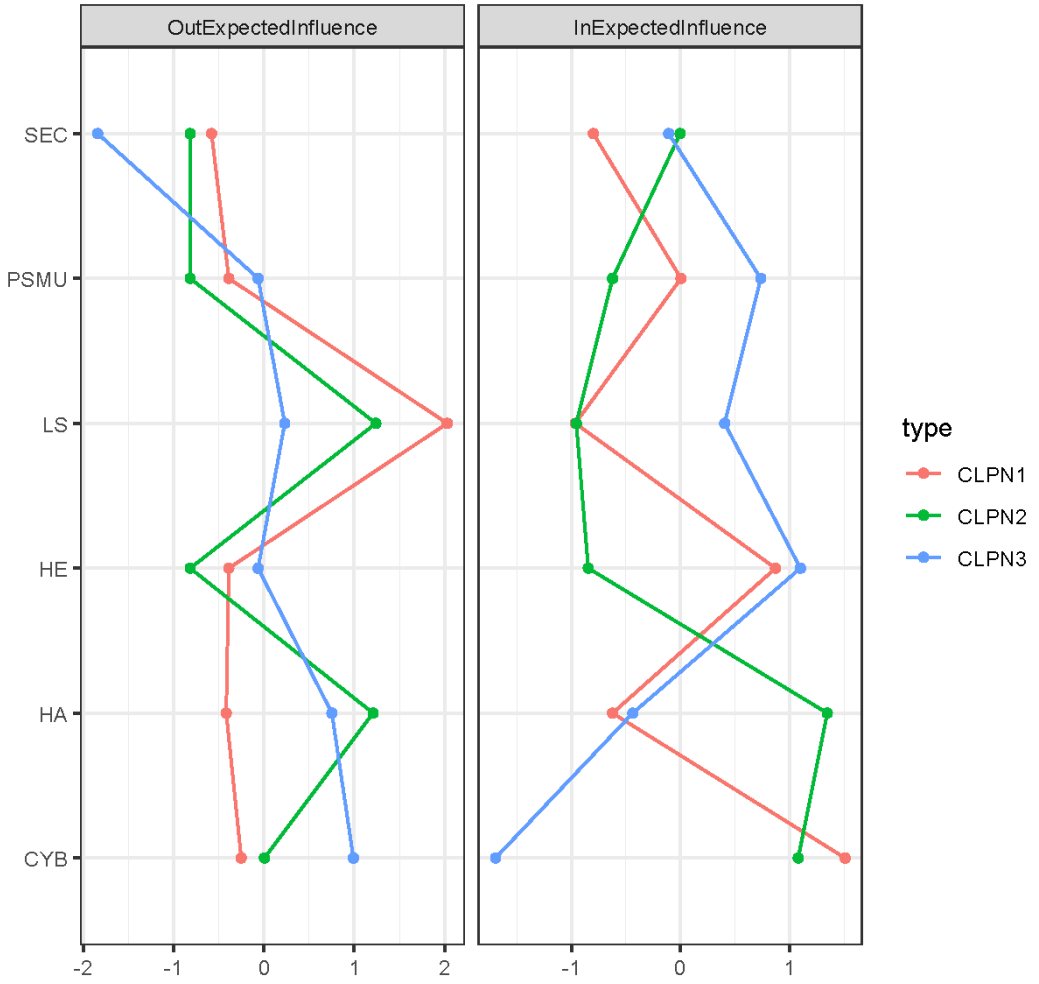
Notably, longitudinal bidirectional paths were identified between cyberchondria and health anxiety in some transition periods. Earlier health anxiety predicted later cyberchondria over the first two intervals (T1 to T2 and T2 to T3), whereas this path was negligible from T3 to T4 and should not be interpreted substantively. From T1 to T2, cyberchondria in T2 was positively predicted by health anxiety in T1 (β = .092), and negatively predicted by security in T1 (β = −.006). Cyberchondria in T1 positively predicted health anxiety in T2 (β = .012). From T2 to T3, cyberchondria in T3 was positively predicted by health anxiety in T2 (β = .086). Cyberchondria in T2 positively predicted health anxiety (β = .098) in T3, and negatively predicted security (β = −.057) in T3. From T3 to T4, cyberchondria in T4 was positively predicted by health anxiety in T3 (β = .001), and negatively predicted by security in T3 (β = −.050). Cyberchondria in T3 positively predicted health anxiety in T4 (β = .054). It should be noted that some paths with small and negligible coefficients (e.g., security to cyberchondria, β = −.006 in T1 to T2; health anxiety to cyberchondria, β = .001 in T3 to T4) were retained by LASSO but should be interpreted with caution.

Centrality indices, including OutExpectedInfluence (out-EI) and InExpectedInfluence (in-EI), were estimated for the CLPN models (see Figure 6). From T1 to T2, life satisfaction had the highest out-EI, and cyberchondria had the highest in-EI. From T2 to T3, life satisfaction had the highest out-EI, and health anxiety had the highest in-EI. From T3 to T4, cyberchondria had the highest out-EI, and health self-efficacy had the highest in-EI. The CLPN indices are shown in Appendix A5.

The accuracy and stability of the CLPN edge weights were assessed using bootstrapped 95% confidence intervals and case-dropping analyses. The bootstrapped edge-weight accuracy plots are shown in Appendix A6. The CS-coefficients for edge weights were 0.36, 0.28, and 0.36 for the T1–T2, T2–T3, and T3–T4 CLPNs, respectively, indicating marginal stability (Epskamp et al., 2018). Accordingly, small LASSO-retained paths should be interpreted cautiously. However, small, negligible coefficients may also reflect the development of relationships between variables. For example, the small path from cyberchondria to health anxiety in the first interval (T1 to T2, β = .012),

and the negligible reverse path from health anxiety to cyberchondria from T3 to T4 (β = .001), suggest that the longitudinal association between the two constructs may vary depending on the transition period examined.

Figure 6. *CLPN Centrality Indices.*



Discussion

Summary of the Findings

Cyberchondria showed a positive correlation with health anxiety and PSMU, and a negative correlation with security, health self-efficacy, and life satisfaction over time. The most central nodes from T1 to T4 were cyberchondria and health self-efficacy, highlighting their influential roles in the networks. CLPN identified the bidirectional links between cyberchondria and health anxiety over time, as well as links between cyberchondria and broader psychological correlates such as security, PSMU, and life satisfaction. The findings should be understood as describing a broader network of cyberchondria and related psychological variables, within which the cyberchondria-health anxiety association represents a central theoretical focus rather than the sole empirical scope of the model.

Relationship With Previous Findings and Implications

The present study found that cyberchondria was positively correlated with health anxiety and PSMU, consistent with previous studies (Ahorsu et al., 2022; McMullan et al., 2019; Starcevic et al., 2019; Vismara et al., 2020). Most importantly, cyberchondria and health anxiety were the most central nodes in the networks in all four times. CLPN also shows that cyberchondria and health anxiety predicted each other over time. Such results support previous findings of the bidirectional links between these two constructs (Baumgartner & Hartmann, 2011; Singh et al., 2016; Te Poel et al., 2016; White & Horvitz, 2009). The present study further contributes to the understanding of this pair of reciprocal relationships. As shown in Figure 5, there appears to be a cycle from health anxiety to

cyberchondria and back to health anxiety. From T1 to T2, the dominant pathway was from health anxiety to cyberchondria. From T2 to T3, both directions were similar in strength. From T3 to T4, the pathway from cyberchondria back to health anxiety becomes more prominent. This data-driven finding is consistent with the association between health anxiety and information-seeking behaviours proposed in the Cognitive-Behavioural Model of the Development and Persistence of Health Anxiety (Salkovskis et al., 2003). However, because coefficients across intervals of unequal length might not be directly comparable, these patterns of links should be interpreted cautiously.

Similar to previous studies (Ahorsu et al., 2022; Türk Kurtça, 2025), PSMU was positively associated with cyberchondria in the current study. PSMU was positively linked with cyberchondria across all four cross-sectional networks. This result is consistent with previous network analyses that identified an association between cyberchondria and PSMU (Pezzi et al., 2024) or problematic internet use (Starcevic et al., 2019). In the CLPN models, earlier cyberchondria, health anxiety, and later PSMU showed temporally ordered associations. This data-driven finding demonstrates that higher cyberchondria predicts greater health anxiety, which in turn increases PSMU levels.

Positive factors, such as security, health self-efficacy, and life satisfaction, were consistently negatively associated with cyberchondria. Security was the most influential factor associated with cyberchondria, consistent with previous studies (e.g., Liu et al., 2023). Beyond that, the CLPN models in the present study identified bidirectional negative predictive paths between security and cyberchondria in some transitions, although some paths were very small (e.g., security to cyberchondria from T1 to T2). Therefore, further studies are needed to confirm whether this bidirectional relationship exists in different contexts. Furthermore, different from previous studies that identified a positive relationship between cyberchondria and health self-efficacy (Gu et al., 2025), the present study found consistent negative associations between the two. However, this negative relationship was weak and inconsistent in the cross-sectional networks and was not identified in the CLPN models. Health self-efficacy seemed to be more strongly associated with security and life satisfaction than with cyberchondria. Future studies should examine whether additional mediators exist between self-efficacy and cyberchondria. Life satisfaction, another potential protective factor against cyberchondria identified in previous research (Tunç et al., 2023; Mathes et al., 2018), was negatively associated with it in the present study. CLPN models show that life satisfaction was closely linked with security over time. In the earlier waves, life satisfaction had the highest out-EIs, indicating that earlier life satisfaction was the most influential factor in predicting the other variables over time in the longitudinal networks. In other words, life satisfaction might be the starting point in the mechanism of forming cyberchondria, and security might help explain the link between low life satisfaction and cyberchondria (as shown in the T1–T2 model in Figure 5).

Theoretical Implications

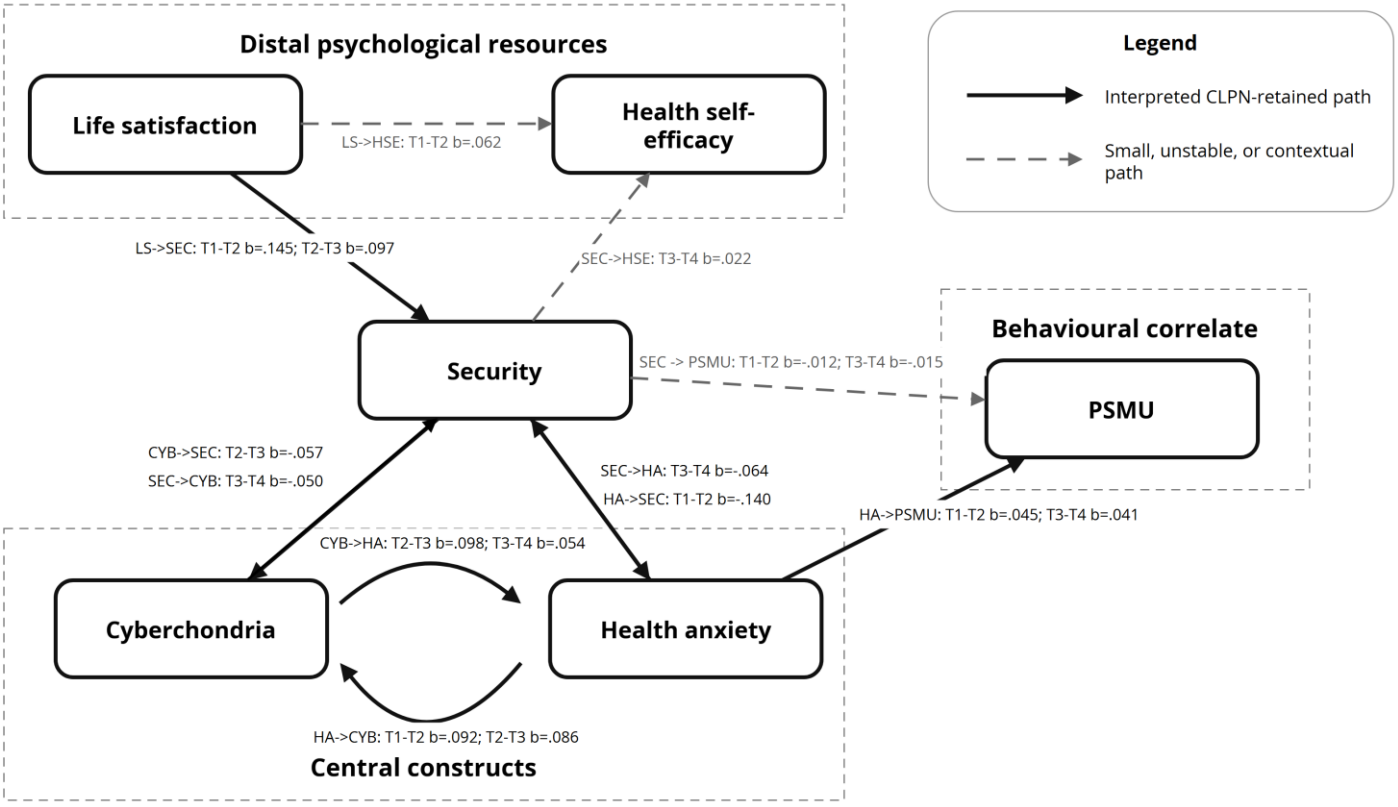
One of the key contributions of this study is its longitudinal design with varying intervals between waves. Previous research used short intervals (one month) due to the rapid decrease of cyberchondria (Song & Min, 2024; Zheng et al., 2022). However, short-interval designs, such as one month, might be limited in explaining true longitudinal effects, as many studies used six-month intervals (e.g., Błoch & Misiak, 2026). The present study included both one-month and six-month intervals to better identify longitudinal links between cyberchondria and its correlates.

Secondly, this study advances theoretical understanding of psychological security's core role in digital health. Existing research mainly emphasises the direct effects of health anxiety or information overload on cyberchondria (Ciułkowicz et al., 2022; Zheng et al., 2023), with limited attention to underlying psychological needs, such as security. Incorporating perceived security as a key factor, this study shows that it was associated with mental health indicators and showed bidirectional predictive relationships with cyberchondria. This finding indicates that individuals' online health behaviours arise from deeper emotional needs, not merely cognitive reactions to health information.

Finally, this study offers dynamic data-based empirical support for the cognitive-behavioural model of health anxiety. Traditional models outline a vicious cycle of health anxiety and safety-seeking behaviours (Salkovskis et al., 2003). Our results not only support the bidirectional predictive link between cyberchondria and health anxiety but also highlight the potential risk factors, such as security and life satisfaction, that can interact with such a link. The conceptual framework of cyberchondria presented in Figure 7 summarises the potential mechanism suggested by the data-driven longitudinal network findings of the present study. The cyberchondria-health anxiety feedback loop persists over time, while perceived security may alleviate health anxiety. Interestingly, both security

and health anxiety prospectively predicted PSMU, suggesting that PSMU may represent a behavioural manifestation of anxiety-driven digital engagement. Broader well-being indicators, such as life satisfaction, may operate as more distal background resources that shape individuals' general psychological resilience.

Figure 7. *CLPN-Based Conceptual Summary of Cyberchondria and Related Correlates.*



Note. Solid arrows indicate CLPN-retained paths with comparatively larger coefficients, as interpreted in the Results. Dashed arrows show paths with small coefficients, inconsistent support, or contextual organisation; these should be interpreted cautiously and not as substantive mechanisms.

Practical Implications

First, this study identifies key intervention targets. Cyberchondria and health self-efficacy exhibited high centrality as critical factors influencing overall psychological well-being, while security and life satisfaction played protective roles in the network. In clinical practice, therapists should not merely focus on limiting social media or internet use but prioritise integrated interventions to directly enhance perceived psychological security, life satisfaction and health self-efficacy, thereby disrupting the maladaptive cyberchondria-health anxiety cycles. Second, the study highlights the importance of early prevention. Data show that low psychological security in the earlier waves predicts subsequent cyberchondria behaviours. This implies that security can serve as a routine screening indicator in university or community mental health services. Timely psychological support should be provided to individuals with low security, even without severe hypochondriac symptoms, to prevent compensatory online behaviours and reduce digital health risks. Moreover, the findings may contribute to public health education development. Given the bidirectional association between cyberchondria and health anxiety, public health authorities should avoid overemphasising disease risks in promotions, as this may activate individuals' anxiety networks and exacerbate their online search behaviours. Instead, efforts should focus on guiding rational interpretation of symptoms, improving public digital health literacy, and enhancing overall life satisfaction.

Limitations and Future Research

This study has several limitations. First, data collection relied on self-report questionnaires, which are susceptible to memory bias and social desirability effects, potentially limiting the objectivity of the results. Future research could employ alternative methods, such as experiments and clinical interviews, to cross-validate subjective and objective measures. Second, the sample primarily consisted of non-clinical individuals in China, limiting the applicability of the findings to clinical populations and other cultural contexts. Future studies should incorporate

clinical samples and conduct cross-cultural comparisons to reveal variations in relationships among variables across different groups and cultures. Furthermore, despite employing the cutting-edge CLPN method, it remains challenging to fully control for confounding variables, such as past medical history. Future research should refine variable definitions and control measures to enhance the rigour of inferences. Because the total scores were used, the CLPN results should be interpreted as reflecting longitudinal relationships among the overall constructs rather than among the specific dimensions of the variables. It should be noted that some variables (e.g., cyberchondria) might have multiple dimensions. Future studies could use the full versions of the scales and test longitudinal relationships among those variables at the item or dimension level. Moreover, the timepoints and intervals stay fairly limited, which may not adequately capture dynamic changes over longer cycles or at higher frequencies. Future research could incorporate methods like ecological momentary assessment to enable intensive tracking in natural settings, thereby more accurately mapping psychological trajectories. Although self-rated health status was collected, it was only reported descriptively and was not included as a covariate in the CLPN analyses in the present study. The present study did not assess the participants' medical conditions or chronic illnesses. These factors may influence cyberchondria and related behaviours, which should be considered and controlled in future studies. Demographic variables, such as age and gender, were not controlled for in the CLPN models because the present study aimed to model the associations among the six constructs, which could be a limitation. Future studies should examine whether demographic variables can influence the networks of cyberchondria and its correlated constructs. Attrition analysis shows that participants who dropped out reported higher cyberchondria, health anxiety, and PSMU, and lower psychological resource variables. Although the effect sizes were small, the results of the present study may not be representative of a larger population. Given that node redundancy checks identified the overlap between cyberchondria and health anxiety in T4, the relevant EI estimates and paths in the final wave should be interpreted with caution. However, the two constructs were retained as separate nodes because they were theoretically distinct concepts and were not identified as redundant across T1 to T3.

Conclusion

Cyberchondria was linked to increased health anxiety and PSMU, along with decreased security, health self-efficacy, and life satisfaction. Long-term bidirectional connections between cyberchondria and health anxiety were identified. The current study identified the relationships between cyberchondria and its positive and negative correlates using a data-driven method, which could be helpful for future hypothesis-testing research.

Conflict of Interest

The authors declare that they have no conflict of interest.

Use of AI Services

The authors declare they have used AI services, specifically Grammarly and Deepseek, for grammar correction and minor style refinements. They carefully reviewed all suggestions from these services to ensure the original meaning and factual accuracy were preserved.

Data Availability Statement

Data will be made available on request.

Authors' Contribution

Yuanli Liu: 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.

Acknowledgement

The present study was funded by the National Social Science Fund of China under grant number 22CSH077.

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

References

Ahorsu, D. K., Lin, C. Y., Alimoradi, Z., Griffiths, M. D., Chen, H. P., Broström, A., Timpka, T., & Pakpour, A. H. (2022). Cyberchondria, fear of COVID-19, and risk perception mediate the association between problematic social media use and intention to get a COVID-19 vaccine. *Vaccines*, *10*(1), Article 122. https://doi.org/10.3390/vaccines10010122

Andreassen, C. S., & Pallesen, S. (2014). Social network site addiction-an overview. *Current Pharmaceutical Design*, *20*(25), 4053–4061. https://doi.org/10.2174/13816128113199990616

Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2017). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviors, 64*, 287–293. https://doi.org/10.1016/j.addbeh.2016.03.006

Arslan, A. (2022). The effect of secondary school students' digital game addictions on self-efficacy levels: A structural equation model study. *E-International Journal of Educational Research, 13*(5), 132–150. https://doi.org/10.19160/e-ijer.1135981

Asmundson, G. J. R., Carleton, N. R., Bovell, C. V., & Taylor, S. (2008). Comparison of unitary and multidimensional models of the Whiteley index in a nonclinical sample: Implications for understanding and assessing health anxiety. *Journal of Cognitive Psychotherapy*, *22*(2), 87–96.https://doi.org/10.1891/0889-8391.22.2.87

Baggio, S., Starcevic, V., Billieux, J., King, D. L., Gainsbury, S. M., Eslick, G. D., &Berle, D. (2022). Testing the spectrum hypothesis of problematic online behaviors: A network analysis approach. *Addictive Behaviors, 135*, Article 107451. https://doi.org/10.1016/j.addbeh.2022.107451

Bahadir, O., & Dundar, C. (2024). The impact of online health information source preference on intolerance to uncertainty and cyberchondria in a youthful generation. *Indian Journal of Psychiatry*, *66*(4),360–366.https://doi.org/10.4103/indianjpsychiatry.indianjpsychiatry_715_23

Bai, X., Wu, C., Zheng, R., & Ren, X. (2011). The psychometric evaluation of the Satisfaction with Life Scale using a nationally representative sample of China. *Journal of Happiness Studies, 12*(2), 183–197. https://doi.org/10.1007/s10902-010-9186-x

Bajcar, B., & Babiak, J. (2021). Self-esteem and cyberchondria: The mediation effects of health anxiety and obsessive–compulsive symptoms in a community sample. *Current Psychology, 40*(6), 2820–2831. https://doi.org/10.1007/s12144-019-00216-x

Baumgartner, S. E., & Hartmann, T. (2011). The role of health anxiety in online health information search. *Cyberpsychology, Behavior, and Social Networking, 14*(10), 613–618. https://doi.org/10.1089/cyber.2010.0425

Błoch, M., & Misiak, B. (2025). Problematic online behaviors and their early patterns of co-occurrence in young adults: Insights from directed and undirected networks. *Frontiers in Psychiatry*, *16*, Article 1446338. https://doi.org/10.3389/fpsyt.2025.1446338

Błoch, M., & Misiak, B. (2026). Loneliness and the emergence of problematic online behaviours in young adults: A cross-lagged panel network analysis. *Comprehensive Psychiatry, 144*, Article 152646. https://doi.org/10.1016/j.comppsych.2025.152646

Capa-Luque, W., Mayorga-Falcón, L. E., Navarro, E. B., Portillo, A. M., Pardavé-Livia, Y., Bazán-Ramírez, A., Hervias-Guerra, E., & Bello-Vidal, C. (2025). Life satisfaction and family communication as protective factors in problematic internet use in university students. *SAGE Open Nursing*, *11*, Article 23779608251350197. https://doi.org/10.1177/23779608251350197

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Ciułkowicz, M., Misiak, B., Szcześniak, D., Grzebieluch, J., Maciaszek, J., & Rymaszewska, J. (2022). The portrait of cyberchondria—a cross-sectional online study on factors related to health anxiety and cyberchondria in Polish population during SARS-CoV-2 pandemic. *International Journal of Environmental Research and Public Health, 19*(7), Article 4347. https://doi.org/10.3390/ijerph19074347

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences (2nd ed.).* Lawrence Erlbaum Associates.

Cong, Z., & An, L. (2004). Developing of security questionnaire and its reliability and validity. *Chinese Mental Health Journal*, *18*(2), 97–99.https://doi.org/10.3321/j.issn:1000-6729.2004.02.010

Diener, E. D., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment, 49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

El-Zoghby, S. M., Zaghloul, N. M., Tawfik, A. M., Elsherbiny, N. M., Shehata, S. A., & Soltan, E. M. (2024). Cyberchondria and smartphone addiction: A correlation survey among undergraduate medical students in Egypt. *Journal of the Egyptian Public Health Association*,*99*(1), Article 7. https://doi.org/10.1186/s42506-024-00154-y

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, *23*(4), 617–634. https://doi.org/10.1037/met0000167

Finney Rutten, L. J., Hesse, B. W., St Sauver, J. L., Wilson, P., Chawla, N., Hartigan, D. B., Moser, R. P., Taplin, S., Glasgow, R., & Arora, N. K. (2016). Health self-efficacy among populations with multiple chronic conditions: The value of patient-centered communication. *Advances in Therapy*, *33*(8), 1440–1451. https://doi.org/10.1007/s12325-016-0369-7

Fried, E. I., Eidhof, M. B., Palic, S., Costantini, G., Huisman-van Dijk, H. M., Bockting, C. L. H., Engelhard, I., Armour, C., Nielsen, A. B. S., & Karstoft, K.-I. (2018). Replicability and generalizability of posttraumatic stress disorder (PTSD) networks: A cross-cultural multisite study of PTSD symptoms in four trauma patient samples. *Clinical Psychological Science*, *6*(3), 335–351. https://doi.org/10.1177/2167702617745092

Funkhouser, C. J., Chacko, A. A., Correa, K. A., Kaiser, A. J., & Shankman, S. A. (2021). Unique longitudinal relationships between symptoms of psychopathology in youth: A cross-lagged panel network analysis in the ABCD study. *Journal of Child Psychology and Psychiatry, 62*(2), 184–194. https://doi.org/10.1111/jcpp.13256

Granero, R., Fernández-Aranda, F., Demetrovics, Z., Ayala-Rojas, R. E., Gómez-Peña, M., Moragas, L., & Jiménez-Murcia, S. (2021). Profile of treatment-seeking gaming disorder patients: A network perspective. *Journal of Gambling Studies, 38*(3), 941–965. https://doi.org/10.1007/s10899-021-10079-2

Gu, C. Y., & Chen, S. B. (2023). Anxiety but hard to escape: A study on health information echo chambers from the perspective of cyberchondria [**焦**虑但难以逃离：网络疑病症视角下的健康信息茧房研究]. *Journal of Modern Information*, *43*(04), 51–63.https://doi.org/10.3969/j.issn.1008-0821.2023.04.006

Gu, C., Qian, L., &Zhuo, X. (2025). Mindfulness intervention for health information avoidance in older adults: Mixed methods study. *JMIR Public Health and Surveillance, 11*, Article e69554. https://doi.org/10.2196/69554

Gustavson, K., Von Soest, T., Karevold, E., & Røysamb, E. (2012). Attrition and generalizability in longitudinal studies: Findings from a 15-year population-based study and a Monte Carlo simulation study.*BMC public health*, *12*(1), Article 918. https://doi.org/10.1186/1471-2458-12-918

Hou, Y., Xiong, D., Jiang, T., Song, L., & Wang, Q. (2019). Social media addiction: Its impact, mediation, and intervention. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace, 13*(1), Article 4.http://dx.doi.org/10.5817/CP2019-1-4

Jiang, S., Li, X., Jin, C., & Liang, Z. (2025). Divergent pathways of mental health symptomatology: A network analysis of adverse childhood experiences and mental health disorders from early to middle adulthood. *Social Science & Medicine*, *384*, Article 118566. https://doi.org/10.1016/j.socscimed.2025.118566

Jokić-Begić, N., Mikac, U., Čuržik, D., & Sangster Jokić, C. (2019). The development and validation of the Short Cyberchondria Scale (SCS). *Journal of Psychopathology and Behavioral Assessment*, *41*(4), 662–676. https://doi.org/10.1007/s10862-019-09744-z

Jungmann, S. M., & Witthöft, M. (2020). Health anxiety, cyberchondria, and coping in the current COVID-19 pandemic: Which factors are related to coronavirus anxiety? *Journal of Anxiety Disorders, 73*, Article 102239. https://doi.org/10.1016/j.janxdis.2020.102239

Lachmann, B., Sariyska, R., Kannen, C., Cooper, A., & Montag, C. (2016). Life satisfaction and problematic Internet use: Evidence for gender specific effects. *Psychiatry Research*, *238*, 363–367. https://doi.org/10.1016/j.psychres.2016.02.017

Lee, S. Y., Hwang, H., Hawkins, R., & Pingree, S. (2008). Interplay of negative emotion and health self-efficacy on the use of health information and its outcomes. *Communication Research, 35*(3), 358–381. https://doi.org/10.1177/0093650208315962

Li, Y., Li, J., Zhou, C., Huang, C., Luo, B., Hu, Y., Huang, X., & Fang, J. (2024). Unraveling the relationships among pandemic fear, cyberchondria, and alexithymia after China's exit from the zero-COVID policy: Insights from a multi-center network analysis. *Frontiers in Psychiatry*,*15*, Article 1489961.https://doi.org/10.3389/fpsyt.2024.1489961

Liu, Y., Peng, W., Cao, M., Zhang, S., Peng, J., & Zhou, Z. (2023). Cyberchondria and Chinese adolescent mental health in the age of COVID-19 pandemic. *Cyberpsychology, Behavior, and Social Networking*, *26*(8), 631–639. https://doi.org/10.1089/cyber.2022.0319

Mathes, B. M., Norr, A. M., Allan, N. P., Albanese, B. J., & Schmidt, N. B. (2018). Cyberchondria: Overlap with health anxiety and unique relations with impairment, quality of life, and service utilization. *Psychiatry Research*, *261*, 204–211. https://doi.org/10.1016/j.psychres.2018.01.002

McElroy, E., Kearney, M., Touhey, J., Evans, J., Cooke, Y., & Shevlin, M. (2019). The CSS-12: Development and validation of a short-form version of the cyberchondria severity scale. *Cyberpsychology, Behavior, and Social Networking*, *22*(5), 330–335. https://doi.org/10.1089/cyber.2018.0624

McMullan, R. D., Berle, D., Arnáez, S., & Starcevic, V. (2019). The relationships between health anxiety, online health information seeking, and cyberchondria: Systematic review and meta-analysis. *Journal of Affective Disorders*,*245*, 270–278. https://doi.org/10.1016/j.jad.2018.11.037

Menon, V., Kar, S. K., Tripathi, A., Nebhinani, N., & Varadharajan, N. (2020). Cyberchondria: Conceptual relation with health anxiety, assessment, management and prevention. *Asian Journal of Psychiatry*,*53*, Article 102225. https://doi.org/10.1016/j.ajp.2020.102225

Merluzzi, T. V., & Martinez Sanchez, M. A. (1997). Assessment of self-efficacy and coping with cancer: Development and validation of the Cancer Behavior Inventory.*Health Psychology*, *16*(2), 163–170. https://doi.org/10.1037//0278-6133.16.2.163

Mestre-Bach, G., & Potenza, M. N. (2023). Cyberchondria: A concern during the covid-19 pandemic and a possible addictive disorder? *Current Addiction Reports*, *10*(1), 77–96. https://doi.org/10.1007/s40429-022-00462-3

Misiak, B. (2025). Cognitive processes and pathways between social isolation, loneliness, and paranoia: Findings from a cross-lagged network analysis of population-based data. *Psychological Medicine*, *55*, Article e215.https://doi.org/10.1017/s003329172510130x

Nadeem, F., Malik, N. I., Atta, M., Ullah, I., Martinotti, G., Pettorruso, M., Vellante, F., Di Giannantonio, M., & De Berardis, D. (2022). Relationship between health-anxiety and cyberchondria: Role of metacognitive beliefs. *Journal of Clinical Medicine*, *11*(9), Article 2590. https://doi.org/10.3390/jcm11092590

Pepe, O., Dalbudak, İ., Atar, Ö., Koçyiğit, B., & Dindar, M. D. (2025). The impact of health anxiety on life satisfaction among male university students in sports sciences. *Journal of Men's Health*, *21*(5), 56–62. https://doi.org/10.22514/jomh.2025.068

Pezzi, M., Zagaria, A., Miguel-Alvaro, A., Gámez-Guadix, M., Gori, A., Santoro, G., & Musetti, A. (2024). Maladaptive daydreaming and problematic online behaviors: A network analysis approach. *Journal of Psychiatric Research*, *177*, 314–320. https://doi.org/10.1016/j.jpsychires.2024.07.023

Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology, 125*(6), Article 747.https://doi.org/10.1037/abn0000181

Salkovskis, P. M., Warwick, H. M., & Deale, A. C. (2003). Cognitive-behavioral treatment for severe and persistent health anxiety (hypochondriasis). *Brief Treatment and Crisis Intervention, 3*(3), 353–367. https://doi.org/10.1093/brief-treatment/mhg026

Seçer, E., & Sevinç Yılmaz, D. (2025). Effects of anxiety and intolerance to uncertainty on life satisfaction among active athletes during COVID-19 period. *Research in Sports Science, 15*, Article 0002. https://doi.org/10.5152/rss.2025.25002

Singh, K., & Brown, R. J. (2014). Health-related internet habits and health anxiety in university students. *Anxiety, Stress, & Coping, 27*(5), 542–554. https://doi.org/10.1080/10615806.2014.888061

Singh, K., Fox, J. R. E., & Brown, R. J. (2016). Health anxiety and internet use: A thematic analysis. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, *10*(2), Article 4. https://doi.org/10.5817/CP2016-2-4

Song, Y., & Min, D. (2024). The logic behind cyberchondria: Longitudinal relations among risk perception, health anxiety, and online health information seeking. *Journal of the Association for Information Science and Technology, 76*(3), 545–562.https://doi.org/10.1002/asi.24946

Starcevic, V. (2017). Cyberchondria: Challenges of problematic online searches for health-related information. *Psychotherapy and Psychosomatics, 86*(3), 129–133. https://doi.org/10.1159/000465525

Starcevic, V., & Berle, D. (2013). Cyberchondria: Towards a better understanding of excessive health-related Internet use. *Expert Review of Neurotherapeutics*, *13*(2), 205–213. https://doi.org/10.1586/ern.12.162

Starcevic, V., Baggio, S., Berle, D., Khazaal, Y., & Viswasam, K. (2019). Cyberchondria and its relationships with related constructs: A network analysis. *Psychiatric Quarterly, 90*(3), 491–505. https://doi.org/10.1007/s11126-019-09640-5

Starcevic, V., Schimmenti, A., Billieux, J., & Berle, D. (2021). Cyberchondria in the time of the COVID-19 pandemic. *Human Behavior and Emerging Technologies, 3*(1), 53–62. https://doi.org/10.1002/hbe2.233

Steinhausen, H. C., Spitz, A., Aebi, M., Metzke, C. W., & Walitza, S. (2020). Selective attrition does not affect cross-sectional estimates of associations with emotional and behavioral problems in a longitudinal study with onset in adolescence. *Psychiatry Research*, *284*, Article 112685. https://doi.org/10.1016/j.psychres.2019.112685

Tang, E., & Lee, W. (2006). Singapore internet users' health information search: Motivation, perception of information sources, and self-efficacy. In M. Murero & R. E. Rice (Eds.), *Internet and health care* (pp. 107–126). Lawrence Erlbaum Associates.

Te Poel, F., Baumgartner, S. E., Hartmann, T., & Tanis, M. (2016). The curious case of cyberchondria: A longitudinal study on the reciprocal relationship between health anxiety and online health information seeking. *Journal of Anxiety Disorders, 43*, 32–40. https://doi.org/10.1016/j.janxdis.2016.07.009

Tunç, T., Demirci, H. F., & Şahin, M. (2023). The relationship between life satisfaction and cyberchondria in the pandemic period. *Black Sea Journal of Health Science*, *6*(4), Article 534542. https://doi.org/10.19127/bshealthscience.1250641

Türk Kurtça, T. (2025). Generalized anxiety disorder and social media addiction relationships: the role of psychological resilience, doomscrolling and cyberchondria severity. *Psihologija, 58*(3), 319–342. https://doi.org/10.2298/PSI230921004T

Vismara, M., Caricasole, V., Starcevic, V., Cinosi, E., Dell'Osso,B., Martinotti, G., & Fineberg, N. A. (2020). Is cyberchondria a new transdiagnostic digital compulsive syndrome? A systematic review of the evidence. *Comprehensive Psychiatry, 99*, Article 152167. https://doi.org/10.1016/j.comppsych.2020.152167

Vujić, A., Volarov, M., Latas, M., Demetrovics, Z., Kiraly, O., & Szabo, A. (2023). Are cyberchondria and intolerance of uncertainty related to smartphone addiction? *International Journal of Mental Health and Addiction*,*22*(6), 3361–3379. https://doi.org/10.1007/s11469-023-01054-6

Wang, R. N., Zhang, Y. C., Wu, R. K., Li, B., Li, C. W., Yu, B. T., & Zhang, Y. L. (2021). A study of self-precaution against the background of the COVID-19 pandemic from the perspective of risk perception attitude theory and social support. *BMC Public Health, 21*(1), Article 1527. https://doi.org/10.1186/s12889-021-11597-9

Wei, X., Zhuang, M., & Xue, L. (2023). Father presence and resilience of Chinese adolescents in middle school: Psychological security and learning failure as mediators. *Frontiers in Psychology*, *13*, Article 1042333. https://doi.org/10.3389/fpsyg.2022.1042333

White, R. W., & Horvitz, E. (2009). Cyberchondria: Studies of the escalation of medical concerns in web search. *ACM Transactions on Information Systems, 27*(4), Article 37. https://doi.org/10.1145/1629096.1629101

Wysocki, A., van Bork, R., Cramer, A. O. J., & Rhemtulla, M. (2022). *Cross-lagged network models*. PsyArXiv. https://doi.org/10.31234/osf.io/vjr8z

Yang, S.Y. (2020). Effects of self-efficacy and self-control on internet addiction in middle school students: A social cognitive theory-driven focus on the mediating influence of social support. *Child Health Nursing Research*, *26*(3), 357–365. https://doi.org/10.4094/chnr.2020.26.3.357

Zhang, J., Zhang, X., Hu, F., Li, K., Luo, M., Yu, Y., & Feng, Z. (2025). Differential directional effects between insomnia symptoms and suicidal ideation across trait depression levels: A cross-lagged network analysis among Chinese medical undergraduates. *Frontiers in Psychiatry*, *16,* Article 1581827. https://doi.org/10.3389/fpsyt.2025.1581827

Zhao, Z., & Kou, Y. (2024). Effects of short video addiction on college students' physical activity: The chain mediating role of self-efficacy and procrastination. *Frontiers in Psychology*, *15*, Article 1429963. https://doi.org/10.3389/fpsyg.2024.1429963

Zheng, H., Chen, X., Jiang, S., & Sun, L. (2023). How does health information seeking from different online sources trigger cyberchondria? The roles of online information overload and information trust. *Information Processing & Management*, *60*(4), Article 103364. https://doi.org/10.1016/j.ipm.2023.103364

Zheng, H., Kim, H.K., Sin, S.J., & Theng, Y.L. (2022). Exploring developmental trajectory of cyberchondria over time: A three-wave panel study. *Telematics Informatics, 75*, Article 101892. https://doi.org/10.1016/j.tele.2022.101892

Appendix

Table A1. *Confirmatory Factor Analysis Fit Indices for All Scales Across Four Waves.*

Scale	Wave	χ^2	*df*	CFI	TLI	RMSEA	SRMR
SCS (Cyberchondria)	T1	2.58	2	1.000	.999	.020	.008
SCS (Cyberchondria)	T2	10.14	2	.994	.981	.075	.015
SCS (Cyberchondria)	T3	0.81	2	1.000	1.002	.000	.004
SCS (Cyberchondria)	T4	6.07	2	.997	.991	.053	.012
WI (Health Anxiety)	T1	13.32	4	.996	.987	.057	.013
WI (Health Anxiety)	T2	31.56	6	.990	.974	.077	.023
WI (Health Anxiety)	T3	9.65	4	.998	.992	.044	.012
WI (Health Anxiety)	T4	23.57	6	.993	.983	.064	.020
SHE (Health Self-Efficacy)	T1	15.60	3	.989	.962	.076	.025
SHE (Health Self-Efficacy)	T2	11.79	4	.992	.981	.052	.020
SHE (Health Self-Efficacy)	T3	21.59	4	.980	.950	.078	.027
SHE (Health Self-Efficacy)	T4	4.29	3	.998	.995	.024	.014
BSMAS (PSMU)	T1	20.85	5	.989	.967	.066	.027
BSMAS (PSMU)	T2	33.66	7	.982	.961	.073	.030
BSMAS (PSMU)	T3	29.82	6	.984	.960	.074	.025
BSMAS (PSMU)	T4	27.69	6	.984	.960	.071	.021
SQ (Security)	T1	408.07	99	.950	.940	.066	.037
SQ (Security)	T2	405.29	102	.954	.946	.064	.035
SQ (Security)	T3	396.51	100	.951	.941	.064	.037
SQ (Security)	T4	405.19	102	.950	.941	.064	.035
SWLS (Life Satisfaction)	T1	20.74	4	.992	.980	.076	.016
SWLS (Life Satisfaction)	T2	6.30	4	.999	.998	.028	.007
SWLS (Life Satisfaction)	T3	8.01	4	.998	.996	.037	.008
SWLS (Life Satisfaction)	T4	24.43	5	.993	.986	.073	.014

Table A2. *Longitudinal Measurement Invariance.*

		Model Fit Indices						Model Comparison				
Scale	Model	χ^2	*df*	CFI	TLI	RMSEA [90% CI]	SRMR	$\Delta\chi^2$	Δdf	ΔCFI	ΔRMSEA	ΔSRMR
1. Cyberchondria (SCS)												
	Configural	134.0	71	.993	.988	.035 [.026, .044]	.033					
	Metric	148.8	80	.992	.988	.035 [.026, .043]	.037	14.8	9	−.0007	−.0005	+.0046
	Scalar	172.4	92	.991	.988	.035 [.027, .043]	.038	23.6	12	−.0013	+.0003	+.0002
	Strict	177.9	104	.992	.990	.031 [.023, .039]	.038	5.5	12	+.0007	−.0034	+.0002
2. Health Anxiety (WI)												
	Configural	1044.6	207	.943	.924	.075 [.070, .079]	.069					
	Metric	1056.2	222	.943	.929	.072 [.068, .077]	.071	11.6	15	+.0002	−.0027	+.0013
	Scalar	1071.5	240	.943	.935	.069 [.065, .074]	.070	15.3	18	+.0002	−.0029	−.0006
	Strict	1110.6	258	.942	.938	.068 [.064, .072]	.071	39.1	18	−.0014	−.0016	+.0009
3. Health Self−Efficacy (SHE)												
	Configural	491.1	131	.943	.917	.062 [.056, .068]	.042					
	Metric	508.3	143	.942	.923	.059 [.054, .065]	.046	17.2	12	−.0008	−.0022	+.0040
	Scalar	538.5	158	.940	.927	.058 [.052, .063]	.048	3.2	15	−.0024	−.0017	+.0015
	Strict	553.7	173	.940	.934	.055 [.050, .060]	.051	15.2	15	+.0000	−.0025	+.0029
4. PSMU (BSMAS)												
	Configural	683.0	207	.953	.938	.056 [.052, .061]	.061					
	Metric	698.8	222	.953	.942	.055 [.050, .059]	.062	15.8	15	−.0001	−.0019	+.0013
	Scalar	726.1	240	.952	.945	.053 [.049, .057]	.063	27.3	18	−.0009	−.0016	+.0008
	Strict	740.0	258	.953	.949	.051 [.047, .055]	.063	13.8	18	+.0004	−.0021	+.0003
5. Security (SQ)												
	Configural	3822.1	1847	.941	.935	.038 [.037, .040]	.048					
	Metric	3937.0	1892	.939	.935	.039 [.037, .040]	.053	114.9	45	−.0021	+.0002	+.0054
	Scalar	4023.4	1940	.938	.935	.039 [.037, .040]	.053	86.4	48	−.0012	−.0001	−.0001
	Strict	4093.6	1988	.937	.936	.038 [.037, .040]	.054	7.1	48	−.0007	−.0003	+.0010
6. Life Satisfaction (SWLS)												
	Configural	263.6	131	.991	.987	.037 [.031, .044]	.032					
	Metric	283.1	143	.991	.987	.037 [.031, .043]	.034	19.5	12	−.0005	−.0006	+.0018
	Scalar	307.4	158	.990	.988	.036 [.030, .042]	.034	24.2	15	−.0006	−.0007	−.0004
	Strict	354.9	173	.988	.987	.038 [.032, .044]	.035	47.5	15	−.0022	+.0020	+.0012

Note. N = 722. MLR estimator with full information maximum likelihood (FIML). All models include correlated uniquenesses between identical items across the four time points. Invariance criteria (Chen, 2007): ΔCFI > −.010, ΔRMSEA < .015, ΔSRMR < .030 for metric invariance and < .010 for scalar/strict invariance. All six scales achieved strict measurement invariance. χ^2 = Satorra-Bentler scaled chi-square.

Table A3. *Network Matrices From T1 to T4.*

	Cyberchondria	Health_anxiety	Health_efficacy	PSMU	Security	Life_satisfaction	Timepoint
Cyberchondria	0	0.674087	−0.05392	0.170991	−0.03521	−0.03259	T1
Health_anxiety	0.674087	0	−0.03598	0.164955	−0.19362	−0.06461	T1
Health_efficacy	−0.05392	−0.03598	0	−0.01664	0.176479	0.453343	T1
PSMU	0.170991	0.164955	−0.01664	0	−0.17206	−0.03023	T1
Security	−0.03521	−0.19362	0.176479	−0.17206	0	0.256325	T1
Life_satisfaction	−0.03259	−0.06461	0.453343	−0.03023	0.256325	0	T1
Cyberchondria	0	0.632774	−0.01257	0.11237	−0.06559	−0.08954	T2
Health_anxiety	0.632774	0	0	0.204666	−0.19104	−0.07949	T2
Health_efficacy	−0.01257	0	0	−0.01324	0.29505	0.377744	T2
PSMU	0.11237	0.204666	−0.01324	0	−0.21964	0	T2
Security	−0.06559	−0.19104	0.29505	−0.21964	0	0.249433	T2
Life_satisfaction	−0.08954	−0.07949	0.377744	0	0.249433	0	T2
Cyberchondria	0	0.66757	0.028251	0.165567	−0.07656	−0.05049	T3
Health_anxiety	0.66757	0	0	0.160307	−0.20746	−0.03472	T3
Health_efficacy	0.028251	0	0	0.065477	0.34418	0.365424	T3
PSMU	0.165567	0.160307	0.065477	0	−0.19463	−0.02458	T3
Security	−0.07656	−0.20746	0.34418	−0.19463	0	0.318046	T3
Life_satisfaction	−0.05049	−0.03472	0.365424	−0.02458	0.318046	0	T3
Cyberchondria	0	0.595728	−0.00334	0.19856	−0.1081	−0.08844	T4
Health_anxiety	0.595728	0	−0.0222	0.17107	−0.23585	0	T4
Health_efficacy	−0.00334	−0.0222	0	0	0.262875	0.29304	T4
PSMU	0.19856	0.17107	0	0	−0.12375	−0.01515	T4
Security	−0.1081	−0.23585	0.262875	−0.12375	0	0.355755	T4
Life_satisfaction	−0.08844	0	0.29304	−0.01515	0.355755	0	T4

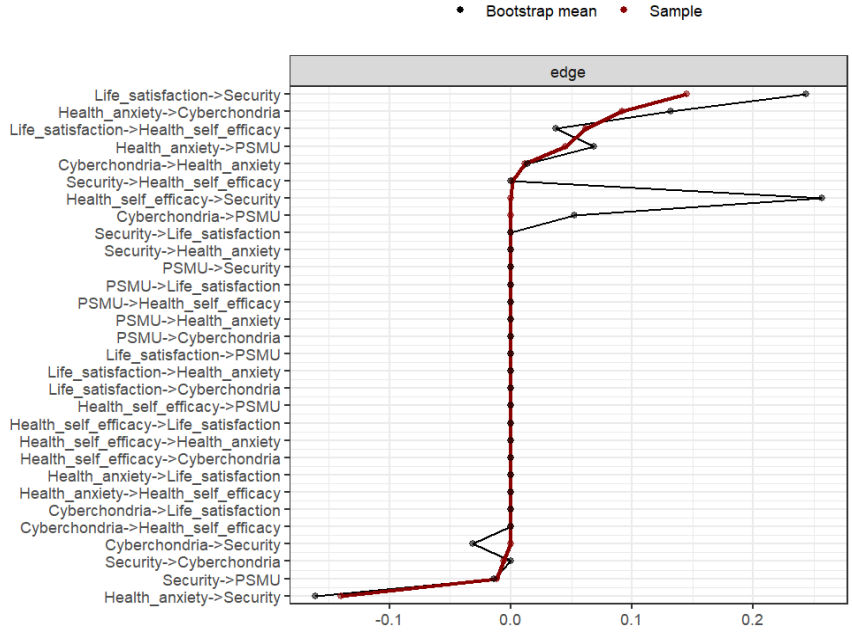
Table A4. *CLPN Matrices.*

T1−T2						
	Cyberchondria T2	Health_anxiety T2	Health_efficacy T2	PSMU T2	Security T2	Life_satisfaction T2
Cyberchondria T1	0	0.012	0	0	0	0
Health_anxiety T1	0.092	0	0	0.045	−0.140	0
Health_efficacy T1	0	0	0	0	0	0
PSMU T1	0	0	0	0	0	0
Security T1	−0.006	0	0.002	−0.012	0	0
Life_satisfaction T1	0	0	0.062	0	0.145	0
T2−T3						
	Cyberchondria T3	Health_anxiety T3	Health_efficacy T3	PSMU T3	Security T3	Life_satisfaction T3
Cyberchondria T2	0	0.098	0	0	−0.057	0
Health_anxiety T2	0.086	0	0	0.014	0	0
Health_efficacy T2	0	0	0	0	0	0
PSMU T2	0	0	0	0	0	0
Security T2	0	0	0	0	0	0
Life_satisfaction T2	0	0	0.005	0	0.097	0
T3−T4						
	Cyberchondria T4	Health_anxiety T4	Health_efficacy T4	PSMU T4	Security T4	Life_satisfaction T4
Cyberchondria T3	0	0.054	0	0	0	0
Health_anxiety T3	0.001	0	0	0.041	0	0
Health_efficacy T3	0	0	0	0	0	0
PSMU T3	0	0	0	0	0	0
Security T3	−0.050	−0.064	0.022	−0.015	0	0.016
Life_satisfaction T3	0	0	0.015	0	0	0

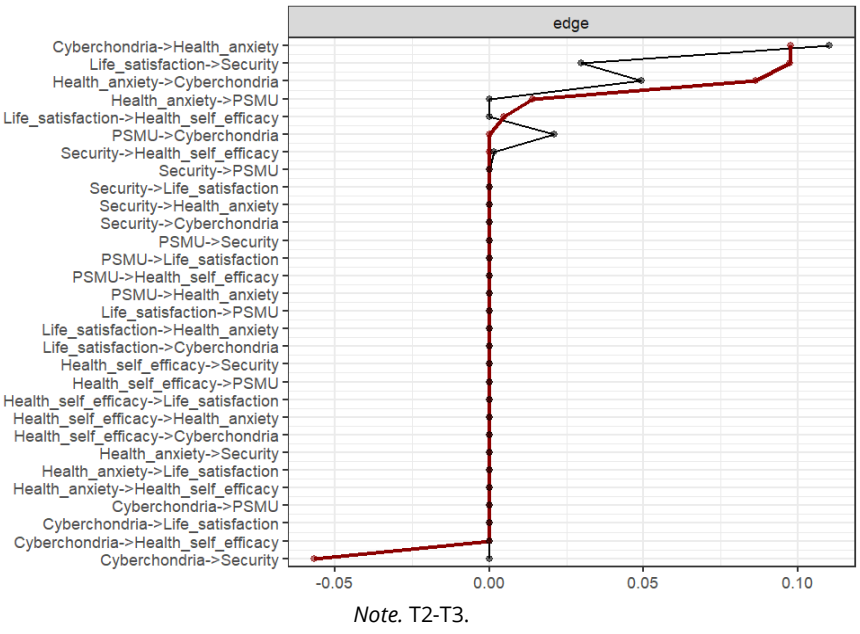
Table A5. *CLPN Centrality Indices.*

Node	Measure	Value	Network
Cyberchondria	OutExpectedInfluence	−0.25193	T1_T2
Health_anxiety	OutExpectedInfluence	−0.41818	T1_T2
Health_efficacy	OutExpectedInfluence	−0.38967	T1_T2
PSMU	OutExpectedInfluence	−0.38967	T1_T2
Security	OutExpectedInfluence	−0.58056	T1_T2
Life_satisfaction	OutExpectedInfluence	2.030005	T1_T2
Cyberchondria	InExpectedInfluence	1.510923	T1_T2
Health_anxiety	InExpectedInfluence	−0.62324	T1_T2
Health_efficacy	InExpectedInfluence	0.87168	T1_T2
PSMU	InExpectedInfluence	0.00435	T1_T2
Security	InExpectedInfluence	−0.79969	T1_T2
Life_satisfaction	InExpectedInfluence	−0.96401	T1_T2
Cyberchondria	OutExpectedInfluence	0.004877	T2_T3
Health_anxiety	OutExpectedInfluence	1.208637	T2_T3
Health_efficacy	OutExpectedInfluence	−0.81743	T2_T3
PSMU	OutExpectedInfluence	−0.81743	T2_T3
Security	OutExpectedInfluence	−0.81743	T2_T3
Life_satisfaction	OutExpectedInfluence	1.238784	T2_T3
Cyberchondria	InExpectedInfluence	1.080465	T2_T3
Health_anxiety	InExpectedInfluence	1.347356	T2_T3
Health_efficacy	InExpectedInfluence	−0.84584	T2_T3
PSMU	InExpectedInfluence	−0.62302	T2_T3
Security	InExpectedInfluence	−0.00313	T2_T3
Life_satisfaction	InExpectedInfluence	−0.95584	T2_T3
Cyberchondria	OutExpectedInfluence	0.990319	T3_T4
Health_anxiety	OutExpectedInfluence	0.75199	T3_T4
Health_efficacy	OutExpectedInfluence	−0.06515	T3_T4
PSMU	OutExpectedInfluence	−0.06515	T3_T4
Security	OutExpectedInfluence	−1.84186	T3_T4
Life_satisfaction	OutExpectedInfluence	0.229846	T3_T4
Cyberchondria	InExpectedInfluence	−1.69662	T3_T4
Health_anxiety	InExpectedInfluence	−0.43767	T3_T4
Health_efficacy	InExpectedInfluence	1.100386	T3_T4
PSMU	InExpectedInfluence	0.736821	T3_T4
Security	InExpectedInfluence	−0.10842	T3_T4
Life_satisfaction	InExpectedInfluence	0.4055	T3_T4

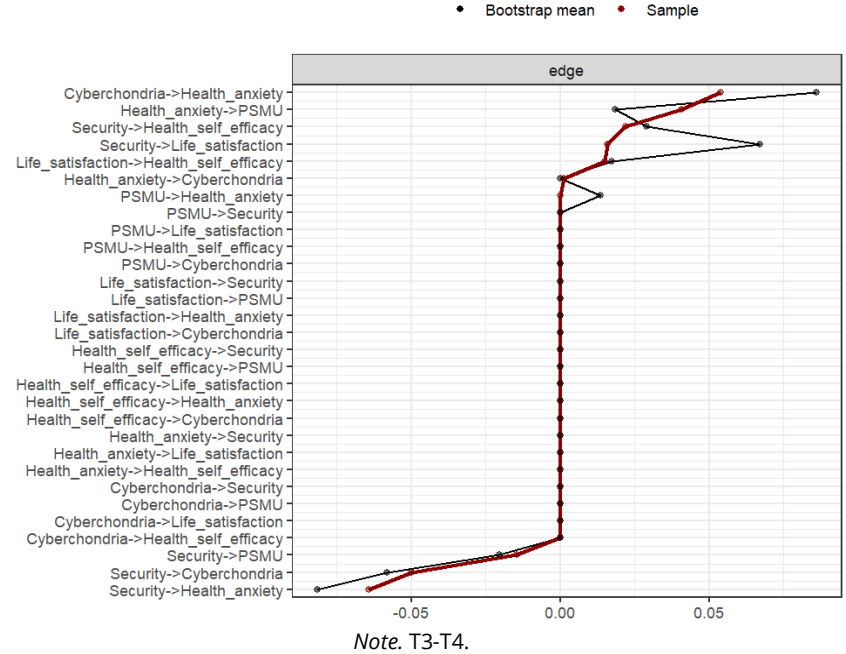
Figure A6. *Edge Weights and Bootstrapped Confidence Intervals of the CLPNs.*



Note. T1-T2.



Note. T2-T3.



Note. T3-T4.

Table A7. *Gender Differences in Cyberchondria and Its Correlates Across the Four Waves.*

Construct	Wave	Male *M* (*SD*)	Female *M* (*SD*)	*t*	*df*	*p*	Cohen's *d*
Cyberchondria	T1	10.87 (4.19)	11.40 (4.25)	−1.66	632.5	.098	−.13
	T2	10.72 (4.12)	11.17 (4.19)	−1.41	634.4	.160	−.11
	T3	10.88 (4.36)	11.14 (4.25)	−0.82	616.6	.414	−.06
	T4	10.18 (4.08)	10.71 (4.21)	−1.69	639.8	.091	−.13
Health anxiety	T1	15.62 (5.92)	15.86 (5.92)	−0.51	627.7	.607	−.04
	T2	15.37 (5.79)	15.39 (5.66)	−0.05	618.4	.962	.00
	T3	15.16 (5.83)	15.07 (5.71)	0.22	618.4	.826	.02
	T4	14.60 (5.86)	14.85 (5.69)	−0.56	615.2	.575	−.04
Health self−efficacy	T1	20.27 (3.03)	19.87 (3.32)	1.68	662.7	.094	.13
	T2	20.54 (2.95)	20.07 (3.31)	2.00	671.0	.046	.15
	T3	20.66 (2.87)	20.51 (3.01)	0.64	646.2	.521	.05
	T4	20.75 (2.77)	20.45 (2.86)	1.42	640.1	.157	.11
Problematic social media use	T1	16.88 (5.29)	17.26 (5.03)	−0.96	606.1	.338	−.07
	T2	17.05 (5.18)	17.12 (5.10)	−0.16	621.1	.869	−.01
	T3	16.74 (5.33)	16.66 (5.17)	0.20	614.6	.839	.02
	T4	16.39 (5.03)	16.62 (5.10)	−0.62	633.2	.533	−.05
Perceived security	T1	59.95 (12.38)	59.63 (12.45)	0.34	629.9	.736	.03
	T2	60.23 (12.90)	59.95 (12.89)	0.29	627.0	.776	.02
	T3	61.15 (12.21)	61.03 (11.94)	0.12	617.9	.901	.01
	T4	61.29 (12.61)	61.28 (11.95)	0.01	604.8	.994	.00
Life satisfaction	T1	22.26 (6.56)	21.70 (6.05)	1.16	592.8	.248	.09
	T2	23.39 (7.27)	23.51 (6.84)	−0.23	601.6	.822	−.02
	T3	23.65 (7.01)	24.05 (6.74)	−0.77	611.1	.441	−.06
	T4	23.28 (7.45)	24.15 (6.90)	−1.59	595.1	.113	−.12

Note. N = 722 (293 male, 429 female).

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