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Health anxiety model of cyberchondria, fears, obsessions, sleep quality, and negative affect during COVID-19

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Abstract
The aim of the study was to explore the relationships among cyberchondria, fear of COVID-19, health anxiety, obsessions, sleep quality, and negative affect in a national community sample of Turkish participants. A sample of 8,276 volunteers, aged between 18 and 65, were recruited via an online platform. The Perceived Vulnerability about Diseases Questionnaire, Fear of COVID-19 Scale, Cyberchondria Severity Scale, Short Health Anxiety Inventory, Depression Stress Anxiety Scale-21, Obsessive–Compulsive Inventory–Revised, and Pittsburgh Sleep Quality Index were completed by participants. Data were analyzed using mixture structural equation modelling approach. Results revealed that perceived vulnerability to disease was found to be positively related with cyberchondria, poor sleep quality, health anxiety, and obsessive–compulsive symptoms. Negative affect was positively associated with obsessive–compulsive symptoms, fears of COVID-19, cyberchondria severity, and poor sleep quality. Additionally, fear of COVID-19 was positively related to health anxiety. Also, cyberchondria severity was found to be positively associated with poor sleep quality and obsessive–compulsive symptoms. Mixture analysis classified participants into six latent classes: 1) Risk-Aversive Healthy Group, 2) Incautious Healthy Group, 3) Infection Obsessions Group, 4) Health Anxiety Group, 5) Negative Affect Group, and 6) General Psychopathology Group. The national survey data showed that perceived vulnerability to diseases, negative affect, fear of COVID-19, cyberchondria, health anxiety, obsessive–compulsive symptoms, and sleep quality appeared to be at the center of pandemic health anxiety.

Keywords Pandemic psychology · Sleep problems · Behavioral addiction · Behavioral immune system · Obsessive–compulsive disorder · Negative affect

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Introduction

A novel coronavirus has rapidly become a pandemic after a cluster of cases first reported in December 2019, in Wuhan, China. The COVID-19 rapidly spread all over the world and has become a public health concern due to its high level of contagion and mortality (Guan et al., 2020). Previously identified vulnerability factors for psychological problems in breakouts include negative affect, anxiety, intolerance to uncertainty, and perceived vulnerability to diseases (Taylor, 2019). Specific fears peculiar to COVID-19 stemming from the uncertainty and novelty of the situation appears to be central in the excessive psychological reactions. (Asmundson & Taylor, 2020). Negative experiences were also reported to be associated with various factors such as shattered safety assumptions about the world, cyberchondria and health anxiety (Scalabrini et al., 2020).

The term health anxiety refers to a set of cognitive features delineated by catastrophic interpretations about body perceptions, perfectionistic hygiene beliefs and perceived lack of control over emergence of diseases (Barsky et al., 1993; Ferguson et al., 2000; Hadjistavropoulos et al., 1998). In a study among 6509 participants in Germany, Petzold et al. (2020) found that approximately 45% of the participants reported fears of being infected by COVID-19, and approximately 68% were apprehensive about the consequences of the coronavirus for their personal lives. Ekiz et al. (2020), in a large sample of 1050 participants, found negative associations between health anxiety and coronavirus control perception. Göksu and Kumcağız (2020) reported that 84% of the participants stated that their anxiety level increased during COVID-19 pandemic. Mertens et al. (2020) identified significant relationships between getting information about coronavirus pandemic through media and social media, health anxiety, and COVID-19 anxiety among 439 community participants recruited from various countries. Addressing different aspects of risk perception in COVID-19, Ding et al. (2020) found that cognitive and affective risk perception in public health crisis were significantly associated with depression, whereas distance perception and positive perception about prevention and control policies were inversely tied to depressive symptoms. In a related investigation, risk perception was found to be varying as a function of gender, age, marital status as well as self-efficacy and imagination (Commodari et al., 2020).

Social distancing has become a vital necessity during COVID-19 pandemic that using Internet for health-related purposes become almost ubiquitous in community samples (Du et al., 2020). Despite several advantages of online health-related searches, because of excessive and unreliable information, those individuals screening on Internet are at risk for eliciting more intense and uncontrollable patterns of maladaptive health-related behaviors called as cyberchondria (Doherty-Torstrick et al., 2016). Cyberchondria serves as a psychological coping mechanism to reduce health-related anxious arousal and assure a sense of safety in the face of health issue; however, Internet searches result in greater anxiety and more intense safety-seeking behaviors in the long term (Fergus, 2014; Norr et al., 2015). Anxiety sensitivity and intolerance of uncertainty are regarded as risk factors for cyberchondria. In an experimental study, it was identified that anxiety sensitivity was the hallmark of individuals with cyberchondriac characteristics (Norr et al., 2014). Fergus (2013) identified in a community sample that intolerance of uncertainty, anxiety sensitivity, and health anxiety were tied to cyberchondria, in which these predictors accounted for approximately half of the unique variance of maladaptive health-related online searches.

Compelling evidence emerged in the literature is that coronavirus fears may cause sleep disturbances. In a representative sample of 16.245 community participants in Germany, Hetkamp et al. (2020) found that 13.5% of the participants reported deterioration in sleep quality, accompanied by generalized anxiety during the coronavirus outbreak. Bigalke et al. (2020) identified that those individuals with poor sleep quality reported higher state anxiety than did individuals with good sleep quality during COVID-19 stay-at-home orders. The coronavirus outbreak was also related to negative affect and obsessive–compulsive behaviors. In keeping with the previous findings, Tzur Bitan et al. (2020) reported positive relationships among fear of COVID-19, depression, anxiety, and stress. In China, prevalence rates of probable obsessive–compulsive disorders in the early stage of the coronavirus pandemic was found to be higher than either middle stage or late stage (Ji et al., 2020). Similarly, in a study with 2004 participants from India, Srivastava et al. (2020) reported that the prevalence rate of obsessions was 13.47% during the COVID-19 pandemic.

Taken together, fear of COVID-19 appears to be associated with a plethora of psychological factors including cyberchondria, health anxiety, negative affect, obsessions, and sleep quality. However, most of the previous studies addressed relationships in part between these potential predictors of pandemic-induced fears. Nevertheless, the associations between an entire set of these variables of interest has still elusive. To this end, the present study was set out to investigate the complex associations between those variables of interest using a mixture structural equation modeling approach. It was speculated that perceived vulnerability to diseases and negative affect would serve as predictor variables in the structural model, in which these variables were associated with sleep quality, obsessive–compulsive symptoms and health anxiety. Those relationships between variables of interest were hypothesized to be mediated by cyberchondria and COVID-19 fears. We also hypothesized that, given the complex relationships between these variables of interest, participants would reveal various patterns of psychological characteristics that would be critical in understanding individual differences in their psychological responses in the face of COVID-19 pandemic. Put succinctly, our main objective in general is to identify the heterogeneity of psychological response patterns during the COVID-19 pandemic that would promote the effectiveness of preventive and curative interventions, particularly related to health anxiety.

Method

Participants and Procedure

In the study, using random sampling procedure based on the nomenclature of territorial units for statistics (NUTS1), 8276 community participants recruited via online crowdsourcing from 12 cities of Turkey (Istanbul, Izmir, Adana, Ankara, Bursa, Gaziantep, Samsun, Kayseri, Balıkesir, Malatya, Trabzon, and Erzurum). We conducted the online research complying with the CHERRIES (Eysenbach, 2004). The e-survey was voluntary only open to invited participants and could only be accessed on a password-protected account. Inclusion criteria were (a) being at an age between 18 and 65 years, (b) having settled permanently in one of 12 cities selected for the NUTS1 at the time of study, (c) giving expected answers to the reliability check questions, and (d) completing all questionnaires. Initially, 21,700 community participants aged between 18 and 65 were randomly invited for the investigation. Approximately 9500 invitations were not responded by the participants. 1730 participants accepted the invitation but not fully completed the psychometric instruments. A sample of 10,470 participants fully completed the socio-demographic questionnaire of the study and psychological variables of interest. However, 2194 respondents were discarded from the data due to inconsistencies within their answers and wrong responses to the control questions.

In a nutshell, those individuals who volunteered and fully completed the socio-demographic questionnaire and psychometric instruments, and who accurately responded to the filler questions for reliability check were included in the study. Responses of randomly selected 400 volunteers were verified via phone call interviews. All volunteers were informed about the study and provided written informed consent. The purpose and procedures of the investigation granted approval from the local ethical committee of the university.

The mean age of the sample was 39.86 (±13.13). Approximately half of the sample were females (47.33%). Majority of volunteers were married (67.85%). Sample characteristics are presented in Table 1.

Psychometric Instruments

In the current investigation, the Perceived Vulnerability about Diseases Questionnaire (PVD-Q), Fear of COVID-19 Scale (FCV-19S), Cyberchondria Severity Scale (CSS-12), Short Health Anxiety Inventory (SHAI), Depression Stress

Table 1 Socio-demographic characteristics of the sample ($N = 8{,}276$)

Age		Mean, SD	39.86	13.13
Gender	Male	n, %	4359	52.67%
	Female	n, %	3917	47.33%
Marital status	Single [¥]	n, %	2661	32.15%
	Married	n, %	5615	67.85%
Education	Primary school	n, %	949	11.47%
	Secondary school	n, %	1632	19.72%
	High school	n, %	3207	38.75%
	Junior college	n, %	718	8.68%
	University	n, %	1584	19.14%
	Graduate school	n, %	186	2.25%
Perceived monthly income	Low	n, %	895	10.81%
	Middle	n, %	5927	71.62%
	Upper	n, %	1454	17.57%
Having a chronic illness		n, %	714	8.63%
Chronic illness among first-degree relatives		n, %	2485	30.03%
Usual bedtime		Median	1:00	-
Usual get up time		Median	8:00	-
Duration of sleep		Mean, SD	7:50	1:28
Time spent on Internet		Mean, SD	4:51	3:18
Time spent on Internet other than work or academic purposes		Mean, SD	2:58	2:30
Poor sleep quality	PSQI ≥ 5	n, %	3838	46.38%
Severe obsessive–compulsive symptoms	OCI-R ≥ 21	n, %	3635	43.92%
Severe depression	DASS-D ≥ 21	n, %	894	10.80%
Severe anxiety	DASS-A ≥ 15	n, %	1104	13.34%
Severe stress	DASS-S ≥ 26	n, %	259	3.13%

[¥] Divorced or widowed individuals (6.01%; $n = 497$) in the sample are categorized as single. *PSQI* Pittsburgh Sleep Quality Index; *OCI-R* Obsessive -Compulsive Inventory -Revised; *DASS* Depression Anxiety Stress Scale -21

Anxiety Scale-21 (DASS-21), Obsessive–Compulsive Inventory-Revised (OCI-R), and Pittsburgh Sleep Quality Index (PSQI) were completed by the volunteered participants.

Perceived Vulnerability about Diseases Questionnaire (PVD-Q)

The PVD-Q is a 15-item self-administered scale originally developed by Duncan et al. (2009) in order to assess one's perceptions about immunity of their own. The PVD-Q yields two subscales of Perceived Infectability and Germ Aversion. The initial development study reported excellent internal reliability, with Cronbach's alphas $\alpha = 0.87$ for Perceived Infectability and $\alpha = 0.74$ for Germ Aversion. The Turkish version revealed excellent reliability, with Cronbach alphas $\alpha = 0.89$ and $\alpha = 0.90$, respectively.

Fear of COVID-19 Scale (FCV-19S)

The FCV-19S is a 7-item self-report scale developed by Ahorsu et al. (2020) to assesses excessive fear of COVID-19. The participants are asked each item to rate on a Likert type scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The psychological instrument assesses a unidimensional construct. The Turkish version was demonstrated to have good reliability and validity by Satici et al. (2020), with a Cronbach's alpha of $\alpha = 0.85$.

Cyberchondria Severity Scale (CSS-12)

The CSS-12 (McElroy et al., 2019) is the shortened version of the 33-item long form of the Cyberchondria Severity Scale which by originally developed by McElroy and Shevlin (2014). Respondents are asked to rate each item on a five-point scale, ranging from 1 (*not at all*) to 5 (*always*). The current data, using Turkish version of the CSS-12, revealed good psychometric characteristics with excellent internal reliability for the overall scale ($\alpha = 0.94$) and four subscales of Excessiveness ($\alpha = 0.80$), Distress ($\alpha = 0.81$), Reassurance ($\alpha = 0.79$), and Compulsion ($\alpha = 0.78$).

Short Health Anxiety Inventory (SHAI)

The SHAI is an 18-item self-report instrument developed by Salkovskis et al. (2002) to assess anxious arousal relevant to health-related anxiety. Higher scores are indicative of greater levels of health anxiety. Respondents are asked to rate each item on a 4-point scale, ranging from 0 to 3. The Turkish version of the SHAI was adapted by Aydemir et al. (2013). The Turkish version was demonstrated to have good validity and reliability, with a Cronbach alpha of $\alpha = 0.92$.

Depression Stress Anxiety Scale -21 (DASS-21)

The DASS-21 is the shortened version of the 42-item long form of the Depression Stress Anxiety Scale both of which were developed by Lovibond and Lovibond (1995). The DASS-21 yields score on three subscales: Depression (DASS-D), Anxiety (DASS-A) and Stress (DASS-S). The cutoff values of the 42-item long for is used to identify individuals that are at greater risk to experience psychological problems. The cutoffs for the subscales of the DASS-21 as follows: DASS-D ≥ 21, DASS-A ≥ 15, and DASS-S ≥ 26 (Lovibond & Lovibond, 2004). The Turkish version of the short form was adapted by Yıldırım et al. (2018). The Turkish version of the DASS-21 revealed good validity and reliability, with high Cronbach alphas for DASS-D ($\alpha = 0.89$), DASS-A ($\alpha = 0.87$), and DASS-S ($\alpha = 0.90$).

Obsessive–Compulsive Inventory – Revised (OCI-R)

The OCI-R was developed by Foa et al. (2002) to assess existence and severity of obsessive–compulsive symptoms. The OCI-R consists of 18 self-report items rated on a five-point scale, ranging from 0 (Not at all) to 4 (Extremely). A cutoff score of 21 or over was suggested in the original development study to identify individuals likely to have obsessive–compulsive disorder. Aydın et al. (2014) reported good validity and reliability for the Turkish version of the OCI-R, with a Cronbach's alpha of $\alpha = 0.89$.

Pittsburgh Sleep Quality Index (PSQI)

The PSQI was developed by Buysse et al. (1989) to assess sleep quality in clinical and nonclinical populations. The PSQI has seven components: Subjective Sleep Quality, Sleep Latency, Sleep Duration, Sleep Efficiency, Sleep Disturbance, Use of Sleep Medication, And Daytime Dysfunction. The greater the scores on the PSQI, the poorer the sleep quality. Ağargün et al. (1996) adapted the Turkish version and showed that the PSQI has good validity and reliability. Using ROC analysis, Yıldırım and Boysan (2017) found that scores on the PSQI ≥ 5 is indicative of poor sleep quality.

Data Analysis

Data analyses were conducted in five steps as follows: i) computing descriptive statistics for socio-demographic characteristics of the sample, ii) testing the Pandemic Health Anxiety Model (PHAM) using the structural equation modeling approach to explore the specified relationships between the variables of interest, iii) identifying the optimal latent class model and classifying participants into respective latent homogenous subgroups by using posterior Bayesian membership probabilities in the mixture model,

iv) exploring the psychological profiles of latent classes by regressing psychological variables (cyberchondria, COVID-19 fears, health anxiety, perceived vulnerability to diseases, obsessive–compulsive symptoms, negative affect, and sleep quality) onto posterior Bayesian membership probabilities, and v) exploring differences in socio-demographic characteristics across latent classes by using the 3-step regression analysis. The Mplus version 8.4 was used in the statistical analyses (Muthén & Muthén, 1998–2017).

As there has been a growing literature addressing the potential psychological outcomes of novel coronavirus, there has been a paucity of national surveys investigating multiple psychological aspects of the pandemic using more sophisticated statistical approaches such as mixture algorithm. Mixture structural equation modeling is a two-step approach (Collins & Lanza, 2010). Firstly, the specified multivariate relationships between variables of interest would be tested using structural equation modelling approach. To avoid from biased estimation, corrected maximum likelihood estimates with standard errors and a chi-square test statistic that are robust to non-normality and non-independence of observations were computed in the structural equation modeling (Satorra & Bentler, 1994, 2001). Normality corrected model fit indices were utilized to test the Pandemic Health Anxiety Model (Bentler, 1990; Bentler & Bonett, 1980; Hooper et al., 2008; Hu & Bentler, 1999; Steiger, 1990). According to the guidelines, acceptable range for the model fit indices are as follows (Hu & Bentler, 1999; Kline, 2015): root mean square error of approximation [RMSEA; 0.05—0.08]; standardized root mean square residual [SRMR; 0.05–0.08]; comparative fit index [CFI; 0.90–0.95], and Tucker-Lewis index [TLI; 0.90–0.95].

The direct and indirect associations between variables of interest, including cyberchondria, fear of COVID-19 infection, health anxiety, perceived vulnerability to diseases, obsessive–compulsive symptoms, negative affect, and sleep quality in the PHAM were specified based on the theoretical explanations and findings of the existing literature. Then, direct and indirect associations among the variables of interest in the specified PHAM were assessed. In the second step of the mixture structural equation modeling, robust maximum likelihood estimates for the associations between variables of interest in the specified PHAM were subjected to mixture modeling latent profile analysis (Collins & Lanza, 2010). In the mixture modeling approach Yuan-Bentler sandwich estimator was utilized (Yuan & Bentler, 2000). To identify the homogeneous subgroups in the sample, optimal number of latent classes were identified based on the maximum likelihood estimates in the PHAM of national survey data. Three information criteria is critical in model comparison of latent class analysis: Akaike Information Criterion [AIC] (Akaike, 1987), Bayesian Information Criterion [BIC] (Schwarz, 1978) and Adjusted Bayesian Information Criterion [ABIC] (Burnham & Anderson, 2004). The lower the information criterion value for the respective latent class model, the better the mixture model fit data (Burnham & Anderson, 2004; Nylund et al., 2007; Preacher & Hayes, 2008). In addition to the information criteria, we used Vuong–Lo–Mendel–Rubin likelihood test and Lo-Mendel-Rubin likelihood test to compare k-class model to k-1-class nested model. Drawn from the parsimonious principle, unsubstantial statistical significance between baseline and nested models ($p > 0.05$) shows that k-1-class model fit the data compared to k-latent-class model (Lo et al., 2001).

In the mixture modeling approach, we computed posterior Bayesian membership probabilities for each participant which are used to classify participants into the optimal homogenous latent classes (Hagenaars, 2009). To provide support for the homogeneity of selected latent class model, average latent class probabilities are computed. *Average latent class probabilities* denote to means of membership probabilities of classified individuals in each latent profile. To ensure acceptable levels of homogeneity in latent profile classification, latent class probabilities for each latent profile should be equal to 0.70 or over (Nagin, 2005). Additionally, we computed entropy index to test the trustworthiness of the selected optimal model. The *entropy index* is an indicator of quality of class membership classification (Celeux & Soromenho, 1996). The entropy index is the summary of posterior probabilities of participants allocated in class k, ranging from 0 to 1. M*plus* uses the relative entropy criterion (Dias & Vermunt, 2006; Wedel & Kamakura, 2000) for the k-class mixture model that rescales the entropy index according to the sample size, ranging from 0.0 to 1.0 (Muthén & Muthén, 1998–2017; Wang & Wang, 2020). An entropy index value greater than 0.80 is suggested to be highly acceptable for homogeneity of latent classes (Clark, 2010), and a value of 0.60 or less is considered as low (Asparouhov & Muthen, 2014; Wang & Wang, 2020).

To identify the profile characteristics of each latent class, we performed regression analyses in which the latent class membership probabilities of each latent class were dependent variable and observed variables in the PHAM were independent variables. The latent classes of optimal mixture model were labeled using the psychological profiles obtained from regression analyses. Finally, we run a 3-step-regression analysis to investigate group differences in socio-demographic variables across latent classes. In the 3-step regression analysis, the latent classes are treated as the dependent variable and independent variables were socio-demographic characteristics of the sample, including age, gender, marital status, education, perceived monthly income, presence of chronical illness, and presence of any chronical illness in the first-degree relatives (Asparouhov & Muthen, 2014; Muthén & Muthén, 1998–2017).

Results

Characteristics of the Sample

The national survey data sample, aged between 18–65 years, were recruited from 12 cities of Turkey based on the NUTS1. The sociodemographic characteristics of the data are presented in Table 1.

As can be seen in Table 1, a sizable minority of the sample (30.03%) reported presence of a chronic illness among their first-degree relatives. On the other hand, 8.63% of the participants had at least one chronic illness. One of the most interesting findings was the high probable caseness of psychopathology in the sample. 46.38% of the sample were poor sleepers as indexed by the PSQI and 43.92% of the sample reported having clinical levels of obsessive–compulsive symptoms as measured by the OCI-R. 10.80% of the participants were likely to have clinical levels of depression and 13.34% of the participants were likely to have clinical levels of anxiety as measured by the DASS-21. These statistics are presented in Table 1.

Psychometric Analyses of Turkish Versions of the CSS-12 and PVD-Q

The CSS-12 and PVD-Q were used to collect data on cyberchondria and perceived vulnerability to diseases in the study. Original English questionnaire forms of these psychometric instruments were translated into Turkish by four scholars. Semantic and cultural equivalence of the measures were evaluated item-by-item basis by the working group of this study. Once a consensus was achieved on the translated items, translation process of the Turkish forms of the CSS-12 and PVD-Q were finalized.

To test the original four-factor latent structure of the CSS-12, the data collected from the sample subjected a confirmatory factor analysis. In the first step, we could not find the factor analytic solution due to the singularity of the identified covariance matrix. Therefore, a second order latent confirmatory factor analytic investigation was converged, in which a general cyberchondria factor was regressed onto the four subscales of the CSS-12. The model fit indices indicated that the second order latent factor structure of the CSS-12 revealed an excellent fit to data as follows: a scaled χ (50) = 458.938 $p < 0.001$; RMSEA [90% confidence interval] = 0.034 [0.031—0.036] $p = 1.000$; CFI = 0.990; TLI = 0.987, and SRMR = 0.015. All items were loaded statistically significantly on the respective factor.

As can be seen in Table 2, the corrected item-total correlation coefficients were excessively high for the total and subscale scores of the CSS-12 (Rjt ≥ 0.60). High item-total correlations are indicative of good construct validity of the psychometric instrument. In addition, we found that a second order general cyberchondria factor along with four first-order latent factors converged in the structural equation modeling. The high item-total correlations supported the premise that a general factor takes place in cyberchondria

Table 2 Descriptive statistics for the psychometric instruments (N = 8,276)

	α	Rjt	Inter-item r	Mean	SD	Mean range (items)	SD range (items)
Cyberchondria Severity Scale—12	0.935	0.685—0.758	0.480- 0.619	30.71	10.90	2.155–3.088	1.036–1.380
Excessiveness	0.796	0.633- 0.650	0.557- 0.578	8.69	3.09	2.677–3.088	1.155–1.324
Distress	0.808	0.648- 0.669	0.573–0.601	7.08	2.89	2.270–2.443	1.036–1.193
Reassurance	0.789	0.608–0.654	0.529–0.588	8.28	3.21	2.155–3.069	1.171–1.380
Compulsion	0.783	0.607- 0.639	0.522–0.564	6.66	2.81	2.170–2.252	1.117–1.126
Perceived Vulnerability to Diseases Scale	0.941	0.660—0.740	0.426–0.623	59.18	19.93	2.966–5.621	1.617–1.952
Perceived Infectability	0.886	0.652–0.700	0.478–0.622	25.03	9.38	2.966–3.991	1.617–1.859
Germ aversion	0.897	0.656–0.720	0.456–0.623	34.15	11.22	3.088–5.621	1.678–1.952
Health Anxiety Inventory	0.937	0.601–0.723	0.381–0.565	15.31	9.94	0.634–1.222	0.729–0.977
Fear of COVID-19 Scale	0.866	0.616—0.682	0.433–0.559	21.43	6.28	2.421–3.711	1.134–1.296
Obsessive–Compulsive Inventory-Revised	0.949	0.636–0.741	0.444–0.587	25.09	14.39	0.970–1.863	0.962–1.254
Depression Anxiety Stress Scale – 21	0.965	0.561- 0.792	0.367–0.652	9.70	12.08	0.245–0.591	0.572–0.893
Depression	0.911	0.709–0.761	0.557–0.636	3.59	4.48	0.431–0.591	0.723–0.893
Anxiety	0.869	0.537–0.720	0.367–0.599	2.53	3.53	0.245–0.461	0.572–0.761
Stress	0.922	0.747–0.770	0.609–0.641	3.58	4.50	0.469–0.558	0.723–0.816
Pittsburgh Sleep Quality Index	0.724	0.118–0.702	-0.021–0.713	4.83	2.98	0.198–1.201	0.539–0.815

N Sample size; *α* internal reliability Cronbach's alfa); *Rjt* Corrected item-total correlations, *Inter-item r* Upper and lower Spearman inter-item correlation coefficients; *Mean* Mean scale scores; *SD* Standard deviations for the scale scores; *Mean range (items)* Upper and lower item means; SD range (items) = Upper and lower item standard deviations even though the construct is multifaceted in nature. Inter-item correlation coefficients were average to strong, ranging from 0.48 to 0.62. The magnitude of inter-item correlations greater than 0.40 can be interpreted as additional robust evidence for the construct validity of the CSS-12. The range of the item correlations did not exceed 0.80, as indicative of lack of content overlaps within items as well. The internal consistency of the total and subscale scores were excellent with Cronbach alphas ranging from $\alpha = 0.78$ to 0.94. The data showed that the Turkish version of the CSS-12 has sound psychometric properties. Psychometric properties of the Turkish version of the CSS-12 are presented in Table 2.

To test the original two-factor latent structure of the PVD-Q, the data collected from the sample subjected a confirmatory factor analysis. The model fit indices indicated that the two-factor latent factor structure of the PVD revealed an excellent fit to data as follows: a scaled χ (89) = 2150.071 $p < 0.001$; RMSEA [90% confidence interval] = 0.056 [0.054—0.058] $p < 0.001$; CFI = 0.957; TLI = 0.949, and SRMR = 0.032.

As can be seen in Table 2, the corrected item-total correlation coefficients were excessively high for the total and subscale scores of the PVD (Rjt ≥ 0.65). High item-total correlations are indicative of good construct validity of the psychometric instrument. Inter-item correlation coefficients were excellent, ranging from 0.66—0.74. High magnitude of inter-item correlations greater than 0.60 can be interpreted as robust evidence for the construct validity of the PVD. Fortunately, the range of the item correlations did not exceed 0.80, which was indicative of lack of content overlaps within items as well. The internal consistency of the total and subscale scores were excellent with Cronbach alphas ranging from $\alpha = 0.89$ to 0.94. The data showed that the Turkish version of the PVD-Q has sound and promising psychometric properties. Psychometric properties of the Turkish version of the PVD-Q are presented in Table 2.

Descriptive Statistics for Psychometric Instruments

The item analyses showed that the psychometric instruments utilized in data collection revealed excellent psychometric properties with high internal reliability, corrected item-total correlation coefficients and inter-item correlation coefficients. The internal consistency, corrected item-total correlation coefficients, inter-item correlation coefficients, item means and item standard deviations along with total and subscale score means and standard deviations are presented in Table 2.

Structural Equation Modeling of the PHAM

To explore the complex relationships between perceived vulnerability to diseases, health anxiety, fear of COVID-19, cyberchondria, obsessive–compulsive symptoms, sleep quality and negative affect in terms of depression, anxiety and stress, we specified a path model throughout the associations among study variables as suggested in previous literature. Accordingly, the specified pathways in the PHAM were tested with Mplus Version 8.4 (Muthén & Muthén, 1998–2017). The minimum fit function maximum likelihood chi-square for the specified model was significant, that scaled $\chi 2$ (9) = 199.418, $p < 0.001$. However, given the sample size of the analysis, other model fit indices revealed that the hypothesized PHAM fit the current data excessively well. The RMSEA, involving the analysis of residuals, was 0.051, $p = 0.426$ [90% confidence interval = 0.045—0.057]. Another residual-based analysis of differences between observed correlation matrix and estimated correlation coefficients is those of that, SRMR was 0.024. The CFI was 0.992, and Tucker-Lewis was 0.983. According to the guidelines the specified model indicated excellent fit the current data. Using software developed by Preacher and Coffman (2006, May), we obtained a power value of 1.00 for the PHAM. Standardized maximum likelihood estimates for the PHAM of Turkish national survey data are presented in Fig. 1.

The PHAM showed that the perceived vulnerability to diseases was significantly associated with cyberchondria severity ($\beta = 0.635$, $p < 0.001$), poor sleep quality ($\beta = 0.175$, $p < 0.001$), health anxiety ($\beta = 0.098$, $p < 0.001$), and obsessive–compulsive symptoms ($\beta = 0.078$, $p < 0.001$), respectively. Negative affectivity as indexed by DASS-21 was significantly tied to obsessive compulsive symptoms ($\beta = 0.780$, $p < 0.001$), fear of COVID-19 ($\beta = 0.457$, $p < 0.001$), cyberchondria severity ($\beta = 0.192$, $p < 0.001$), and poor sleep quality ($\beta = 0.188$, $p < 0.001$), respectively. Fears of COVID-19 was statistically significantly associated with health anxiety ($\beta = 0.359$, $p < 0.001$). Cyberchondria severity was a significant correlate of both poor sleep quality ($\beta = 0.392$, $p < 0.001$) and obsessive–compulsive symptoms ($\beta = 0.081$, $p < 0.001$). The corrected maximum likelihood estimates are presented in Fig. 1.

To explore the indirect associations between the variables of interest in the PHAM, we used bootstrap procedure to obtain bias-corrected estimates. The PHAM was bootstrapped 1000 times to obtain standardized correlation coefficients, standard errors, 95% bias-corrected confidence intervals, critical t values, and p values. The mediation analysis in the PHAM identified that perceived vulnerability to diseases was significantly related to both obsessive–compulsive symptoms (*indirect* $\beta = 0.051$, 95% bias-corrected confidence intervals = 0.040–0.063, $t = 8.462$, $p < 0.001$) and poor sleep quality (*indirect* $\beta = 0.249$, 95% bias-corrected confidence intervals = 0.231–0.266, $t = 28.206$, $p < 0.001$) though cyberchondriac behaviors. Cyberchondria severity also mediated the relationships of negative affectivity with obsessive–compulsive symptoms

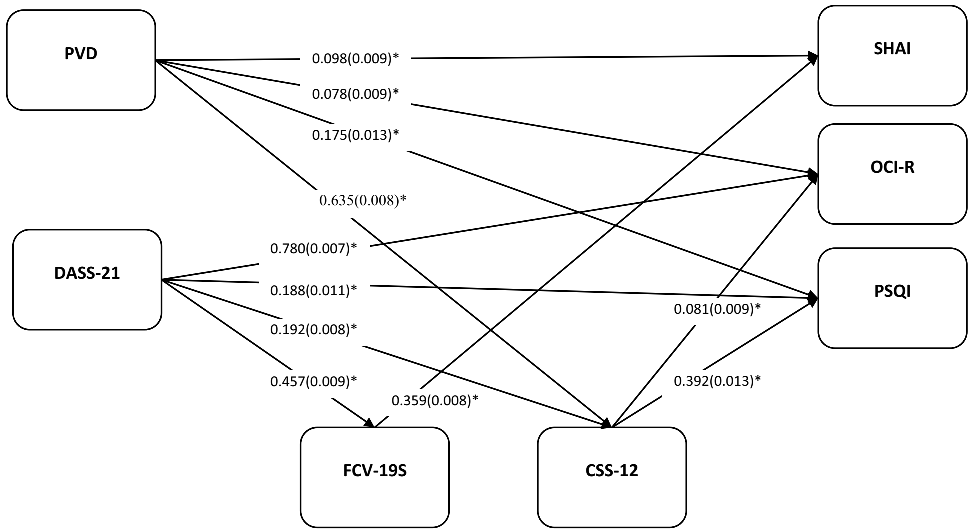

Fig. 1 Structural equation model of Pandemic Health Anxiety Model (N = 8,276). PVD = Perceived Vulnerability about Diseases Questionnaire; CSS-12 = Cyberchondria Severity Scale-12; OCI-R = Obsessive Compulsive Inventory – Revised; PSQI = Pittsburgh Sleep Quality Index; DASS-21 = Depression Anxiety Stress-21; FCV-19S = Fear of COVID-19 Scale; SHAI = Short Healthy Anxiety Inventory. *: $p < 0.01$; β (SE) = Standardized maximum likelihood estimates (Standard error)

(*indirect* $\beta = 0.015$, 95% bias-corrected confidence intervals = 0.012–0.019, $t = 8.065$, $p < 0.001$) and poor sleep quality (*indirect* $\beta = 0.075$, 95% bias-corrected confidence intervals = 0.068–0.083, $t = 19.582$, $p < 0.001$). Negative affectivity statistically significantly contributed to the health anxiety (*indirect* $\beta = 0.164$, 95% bias-corrected confidence intervals = 0.154–0.173, $t = 34.540$, $p < 0.001$) through COVID-19 fears as well. Results of mediation analyses are presented in Table 3.

Mixture Analysis of the PHAM

To explore the specific psychological profiles of homogenous subgroups of individuals based on the relationships among the variables of interest converged on the PHAM, we conducted a latent profile analysis. Beginning from 1-latent-class to 7-latent-class, parameters of the previously converged structural equation model were subjected to mixture analysis to obtain optimal number of latent classes. We computed the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Adjusted Bayesian Information Criteria (ABIC), Vuong-Lo-Mendell-Rubin Likelihood Ratio Test (VLMR), and Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMRT) to determine optimal number of latent classes. The VLML (689.828, $p = 0.0831$) and LMRT (677.315, $p = 0.0863$) showed that 6-latent-class was the optimal model compared to the 7-latent-class model. 6- latent-class model had lower values for information criteria than other models with latent classes less than six (AIC = 247,164.096, BIC = 247,522.172, and ABIC = 247,360.104). The entropy index for the model was 0.901 which showed a high consistency within latent class (> 0.80). In addition, average classification membership probability for each of the latent class was greater than 0.70. The average classification membership probabilities for the latent homogenous subgroups were 0.913, 0.908, 0.928, 0.849, 0.933, and 0.986, respectively. Given the mixture analysis results, we concluded that 6-latent-class model was the optimal model revealing best fit to the current data. Results are presented in Table 4.

The distribution of participants across six latent classes and proportions of subgroups among the sample (N = 8276)

Table 3 Indirect relationships in the Pandemic Healthy Anxiety Model (N = 8,276)

Indirect relationships	Indirect β (SE)	95% Bias-corrected confidence intervals	t	p
PVD ➔ **CSS-12** ➔ OCI-R	0.051 (0.006)	0.040–0.063	8.462	< 0.001
PVD ➔ **CSS-12** ➔ PSQI	0.249 (0.009)	0.231–0.266	28.206	< 0.001
DASS-21 ➔ **FCV-19S** ➔ SHAI	0.164 (0.005)	0.154–0.173	34.540	< 0.001
DASS-21 ➔ **CSS-12** ➔ OCI-R	0.015 (0.002)	0.012–0.019	8.065	< 0.001
DASS-21 ➔ **CSS-12** ➔ PSQI	0.075 (0.004)	0.068–0.083	19.582	< 0.001

The mediator variables in the Pandemic Healthy Anxiety Model are in bold

PVD Perceived Vulnerability about Diseases Questionnaire; *CSS-12* Cyberchondria Severity Scale-12; *OCI-R* Obsessive Compulsive Inventory – Revised; *PSQI* Pittsburgh Sleep Quality Index; *DASS-21* Depression Anxiety Stress-21; *FCV- 19S* Fear of COVID-19 Scale; *SHAI* Short Healthy Anxiety Inventory; β Standardized regression coefficient; *SE* Standard error

Table 4 Model fit indices for the latent profile analysis ($N = 8{,}276$)

Indices	Latent Classes						
	1-latent-class	2-latent-class	3-latent-class	4-latent-class	5-latent-class	6-latent-class	7-latent-class
AIC	404,259.543	250,464.525	249,230.802	248,442.936	247,724.002	247,164.096	246,527.163
BIC	404,505.282	250,654.095	249,462.498	248,716.760	248,039.952	247,522.172	246,927.367
ABIC	404,394.059	250,568.294	249,357.631	248,592.825	247,896.950	247,360.104	246,746.232
Entropy	NA	0.997	0.900	0.879	0.888	0.901	0.906
VLMR	NA	10,958.494	1245.724	799.865	730.934	571.906	**689.828**
P value	NA	< 0.0001	< 0.0001	< 0.0001	0.0023	< 0.0001	**0.0831**
LMR	NA	10,759.707	1223.126	785.356	717.675	561.532	**677.315**
P value	NA	< 0.0001	< 0.0001	< 0.0001	0.0025	< 0.0001	**0.0863**

NA Not applicable; Insubstantial comparison between baseline model and nested model is presented in bold

AIC Akaike Information Criteria; *BIC* Bayesian Information Criteria; *ABIC* Adjusted Bayesian Information Criteria; *VLMR* Vuong-Lo-Mendell-Rubin Likelihood Ratio Test; *LMR* Lo-Mendell-Rubin Adjusted Likelihood Ratio Test

were as follows: latent-class-1 consisted of 1212 individuals ((14.64%), latent-class-2 consisted of 2869 individuals (34.67%), latent-class-3 consisted of 2939 individuals(35.51%), latent-class-4 consisted of 151 individuals (1.82%), latent-class-5 consisted of 166 individuals (2.01%), and latent-class-6 consisted of 939 individuals (11.35%).

Regression Analysis on Posterior Bayesian Posterior Membership Probabilities

To explore psychological characteristics of the latent classes, we carried out regression analyses in which classification membership probability of each latent-class was used as dependent variable. The CSS-12, FCV-19S, SHAI, PVD-Q, OCI-R, DASS-21, and PSQI scores were regressed onto classification membership probability of each latent-class separately. Membership probabilities for the individuals classified into the latent-class 1 was significantly positively associated with PVD-Q ($R^2 = 0.015$, $\beta = 0.122$, $t = 11.187$, $p < 0.001$), but inversely associated with CSS-12 ($R^2 = 0.188$, $\beta = -0.434$, $t = -43.775$, $p < 0.001$), FCV-19S ($R^2 = 0.016$, $\beta = -0.127$, $t = -11.649$, $p < 0.001$), SHAI ($R^2 = 0.023$, $\beta = -0.152$, $t = -14.008$, $p < 0.001$), OCI-R ($R^2 = 0.003$, $\beta = -0.057$, $t = -5.221$, $p < 0.001$), DASS-21 ($R^2 = 0.003$, $\beta = -0.057$, $t = -5.236$, $p < 0.001$), and PSQI ($R^2 = 0.083$, $\beta = -0.287$, $t = -27.291$, $p < 0.001$). Although individuals classified into this latent class were less likely to have psychopathology, individuals classified into latent-class-1 had a tendency to perceive themselves as vulnerable to diseases which may be protective from infection. Therefore, this homogenous subgroup was labeled as '*Risk-Aversive Healthy Group*'.

In the latent-class-2, regression analyses showed that posterior membership probability of the latent class was inversely associated with CSS-12 ($R^2 = 0.001$, $\beta = -0.038$, $t = -3.464$, $p = 0.001$), FCV-19S ($R^2 = 0.667$, $\beta = -0.816$, $t = -128.619$, $p < 0.001$), SHAI ($R^2 = 0.113$, $\beta = -0.335$, $t = -32.393$, $p < 0.001$), PVD ($R^2 = 0.071$, $\beta = -0.266$, $t = -25.052$, $p < 0.001$), OCI-R ($R^2 = 0.118$, $\beta = -0.343$, $t = -33.269$, $p < 0.001$), DASS-21 ($R^2 = 0.144$, $\beta = -0.380$, $t = -37.313$, $p < 0.001$), and PSQI ($R^2 = 0.019$, $\beta = -0.139$, $t = -12.775$, $p < 0.001$). As with the latent class 1, participants in this latent homogenous subgroup were less likely to manifest symptoms of psychopathology, whereas it seemed that those of individuals in this group were more likely perceive themselves as nonvulnerable to diseases. This may render this group more likely to behave in a risky way which may pose risk for these individuals to be more receptive to infections or diseases. So, we labeled this group as '*Incautious Healthy Group*'.

In the third set of regression analyses, we found that membership probabilities of the latent-class-3 was positively significantly associated with CSS-12 ($R^2 = 0.035$, $\beta = 0.186$, $t = 17.232$, $p < 0.001$), FCV-19S ($R^2 = 0.339$, $\beta = 0.582$, $t = 65.139$, $p < 0.001$), OCI-R ($R^2 = 0.082$, $\beta = 0.286$, $t = 27.177$, $p < 0.001$), DASS-21 ($R^2 = 0.080$, $\beta = 0.282$, $t = 26.756$, $p < 0.001$), and PSQI ($R^2 = 0.040$, $\beta = 0.201$, $t = 18.661$, $p < 0.001$). The membership probabilities of the group were inversely significantly associated with SHAI ($R^2 = 0.097$, $\beta = -0.311$, $t = -29.787$, $p < 0.001$) and unsubstantially linked to PVD ($R^2 < 0.001$, $\beta = -0.004$, $t = -0.342$, $p = 0.732$). Fear of COVID-19 was at the hearth of this subgroup along with obsessionality, cyberchondria, negative affect, sleep problems. That is, we labeled this latent homogenous subgroup as '*Infection Obsessions Group*'.

For the latent-class-4, we found that FCV-19S ($R^2 = 0.018$, $\beta = 0.132$, $t = 12.149$, $p < 0.001$), SHAI ($R^2 = 0.123$, $\beta = 0.350$, $t = 34.021$, $p < 0.001$), and PVD ($R^2 = 0.010$, $\beta = 0.099$, $t = 9.085$, $p < 0.001$) were significantly related to membership probabilities of the subgroup. The subgroup was inversely associated with CSS-12 ($R^2 = 0.007$, $\beta = -0.083$, $t = -7.576$, $p < 0.001$) and PSQI

($R^2 = 0.008$, $\beta = -0.087$, $t = -7.920$, $p < 0.001$), and unsubstantially associated with the scores on the OCI-R ($R^2 < 0.001$, $\beta = 0.009$, $t = 0.790$, $p = 0.429$) and DASS-21 ($R^2 < 0.001$, $\beta = 0.012$, $t = 1.137$, $p = 0.256$). This latent subgroup was characterized by fear of COVID-19, health anxiety and perceived vulnerability to diseases which was labeled as '*Health Anxiety Group*'.

In the fifth set of regressions, it was found that individuals classified into latent-class-5 were more likely to report greater scores on the CSS-12 ($R^2 = 0.003$, $\beta = 0.053$, $t = 4.803$, $p < 0.001$), FCV-19S ($R^2 = 0.008$, $\beta = 0.092$, $t = 8.395$, $p < 0.001$), SHAI ($R^2 = 0.017$, $\beta = 0.132$, $t = 12.134$, $p < 0.001$), PVD ($R^2 = 0.004$, $\beta = 0.062$, $t = 5.660$, $p < 0.001$), DASS-21 ($R^2 = 0.016$, $\beta = 0.125$, $t = 11.451$, $p < 0.001$), and PSQI ($R^2 = 0.009$, $\beta = 0.093$, $t = 8.483$, $p < 0.001$). The relationship between group membership probabilities and the OCI-R scores was not significant ($R^2 < 0.001$, $\beta = 0.009$, $t = 0.777$, $p = 0.437$). The participants in the latent-class-5 were characterized by occurrence of all types of psychological symptoms to an extent except for obsessive–compulsive symptoms. Hence, this homogenous subset of individuals was labeled as '*Negative Affect Group*'.

Finally, membership probabilities of the latent-class-6 were positively significantly tied to the CSS-12 ($R^2 = 0.067$, $\beta = 0.260$, $t = 24.454$, $p < 0.001$), FCV-19S ($R^2 = 0.136$, $\beta = 0.368$, $t = 36.043$, $p < 0.001$), SHAI ($R^2 = 0.753$, $\beta = 0.868$, $t = 158.898$, $p < 0.001$), PVD ($R^2 = 0.033$, $\beta = 0.183$, $t = 16.913$, $p < 0.001$), OCI-R ($R^2 = 0.018$, $\beta = 0.133$, $t = 12.168$, $p < 0.001$), DASS-21 ($R^2 = 0.020$, $\beta = 0.140$, $t = 12.852$, $p < 0.001$), and PSQI ($R^2 = 0.045$, $\beta = 0.212$, $t = 19.724$, $p < 0.001$). Severe health anxiety was at the hearth of this homogenous subset co-occurring with all other psychological symptoms. Therefore, the latent class 6 was labeled as '*General Psychopathology Group*'. Findings are presented in Table 5.

3-Step Regression Analyses

To explore the differences in socio-demographic variables across latent classes, we carried out 3-step regression analyses. In the 3-step regression analysis, sociodemographic variables (age, gender, marital status, education, perceived monthly income, having a chronic illness, and chronic illness among first-degree relatives) were regressed onto 6-latent classes. We found that individuals classified into Negative Affect Group were younger than all other latent homogenous subgroups. Risk-Aversive Healthy individuals were also younger than all other subgroups, but those individuals classified into the Negative Affect subgroup. As compared to Risk-Aversive Healthy Group and Incautious Healthy Group, individuals classified into General Psychopathology Group consisted of females. Individuals with Infection Obsessions were more likely to be female than those of individuals classified into Incautious Healthy Group. Individuals in the Negative Affect Group were more likely to be single compared to other five homogenous latent subgroups. Negative Affect Group reported greater levels of education than all other five latent classes. The proportions of individuals with at least one chronic illness did not significantly differ across six latent classes. On the other hand, individuals classified into Negative Affect Group were more likely to report at least one chronic illness among their first-degree relatives in comparison to other five latent homogenous subgroups. Risk-Aversive Healthy individuals reported greater rates of chronic illnesses among their relatives than Incautious Healthy individuals. To put succinctly, of these six latent classes, participants classified into Negative Affect Group were characterized by being single, being younger of age, having higher of education and having first-degree relatives with at least one chronic illness. The main distinction of Risk-Aversive Healthy latent class from the Incautious Healthy latent class was that having first-degree relatives with at least one chronic illness. Finally, females appeared to have greater risk for having psychopathology. Findings are presented in Table 6.

Discussion

The National Survey of Pandemic Health Anxiety was conducted in a representative sample of 8276 participants recruited according to the NUTS1 from 12 cities in Turkey. The associations between fear of COVID-19, cyberchondria, health anxiety, affective symptoms, obsessive–compulsive symptoms, and sleep quality were examined using mixture structural equation modeling approach. The structural analysis of the PHAM showed that perceived vulnerability to diseases and negative affect including depression and anxiety significantly contributed to health anxiety, obsessive–compulsive symptoms, and poor sleep quality. These relationships were mediated by cyberchondria and fear of COVID-19 in the structural model. As mentioned above, in keeping with the literature, we supported and expanded the previous findings with respect to the scientific research on psychological functioning during COVID-19 pandemic. However, in the literature, relationships between the variables of interest addressed in the current data have not been investigated in such an extensive way. This study would be a preliminary one addressing the relationships between all these seven psychological variables using an advanced statistical approach of mixture structural equation modeling. Finally, the mixture model indicated the heterogeneity of associations between variables of interest. Six latent classes were extracted in the mixture analysis: 1) Risk-Aversive Healthy Group ($n = 1212$, 14.64%); 2) Incautious Healthy Group ($n = 2869$, 34.67%); 3) Infection Obsessions Group ($n = 2939$, 35.51%); 4) Health

Table 5 Regression analyses of psychological variables on posterior membership probabilities of latent profiles ($N = 8,276$)

	Latent Profile 1 Risk-Aversive Healthy Group *n* = 1212, 14.64%				Latent Profile 2 Incautious Healthy Group *n* = 2869, 34.67%				Latent Profile 3 Infection Obsessions Group *n* = 2939, 35.51%			
	R^2	β	t	P	R^2	β	t	P	R^2	β	t	P
Cyberchondria Severity Scale	0.188	-0.434	-43.775	*< 0.001*	0.001	-0.038	-3.464	0.001	**0.035**	**0.186**	**17.232**	***< 0.001***
Fear of COVID-19 Scale	0.016	-0.127	-11.649	*< 0.001*	0.667	-0.816	-128.619	*< 0.001*	**0.339**	**0.582**	**65.139**	***< 0.001***
Short Health Anxiety Inventory	0.023	-0.152	-14.008	*< 0.001*	0.113	-0.335	-32.393	*< 0.001*	0.097	-0.311	-29.787	*< 0.001*
Perceived Vulnerability to Diseases Questionnaire	**0.015**	**0.122**	**11.187**	***< 0.001***	0.071	-0.266	-25.052	*< 0.001*	< 0.001	-0.004	-0.342	0.732
Obsessive Compulsive Inventory—Revised	0.003	-0.057	-5.221	*< 0.001*	0.118	-0.343	-33.269	*< 0.001*	**0.082**	**0.286**	**27.177**	***< 0.001***
Depression Anxiety Stress Scale- 21	0.003	-0.057	-5.236	*< 0.001*	0.144	-0.380	-37.313	*< 0.001*	**0.080**	**0.282**	**26.756**	***< 0.001***
Pittsburgh Sleep Quality Index	0.083	-0.287	-27.291	*< 0.001*	0.019	-0.139	-12.775	*< 0.001*	**0.040**	**0.201**	**18.661**	***< 0.001***

	Latent Profile 4 Health Anxiety Group *n* = 151, 1.82%				Latent Profile 5 Negative Affect Group *n* = 166, 2.01%				Latent Profile 6 General Psychopathology Group *n* = 939, 11.35%			
	R^2	β	t	P	R^2	β	t	P	R^2	β	t	P
Cyberchondria Severity Scale	0.007	-0.083	-7.576	*< 0.001*	**0.003**	**0.053**	**4.803**	***< 0.001***	**0.067**	**0.260**	**24.454**	***< 0.001***
Fear of COVID-19 Scale	**0.018**	**0.132**	**12.149**	***< 0.001***	**0.008**	**0.092**	**8.395**	***< 0.001***	**0.136**	**0.368**	**36.043**	***< 0.001***
Short Health Anxiety Inventory	**0.123**	**0.350**	**34.021**	***< 0.001***	**0.017**	**0.132**	**12.134**	***< 0.001***	**0.753**	**0.868**	**158.898**	***< 0.001***
Perceived Vulnerability to Diseases Questionnaire	**0.010**	**0.099**	**9.085**	***< 0.001***	**0.004**	**0.062**	**5.660**	***< 0.001***	**0.033**	**0.183**	**16.913**	***< 0.001***
Obsessive Compulsive Inventory—Revised	< 0.001	0.009	0.790	0.429	< 0.001	0.009	0.777	0.437	**0.018**	**0.133**	**12.168**	***< 0.001***
Depression Anxiety Stress Scale- 21	< 0.001	0.012	1.137	0.256	**0.016**	**0.125**	**11.451**	***< 0.001***	**0.020**	**0.140**	**12.852**	***< 0.001***
Pittsburgh Sleep Quality Index	0.008	-0.087	-7.920	*< 0.001*	**0.009**	**0.093**	**8.483**	***< 0.001***	**0.045**	**0.212**	**19.724**	***< 0.001***

Positive significant correlates of the latent profiles are in bold

Table 6 Demographic profiles of the latent classes (N=8,276)

	Risk-Aversive Healthy n=1212		Incautious Healthy n=2869		Infection Obsessions n=2939		Health Anxiety n=151		Negative Affect n=166		General Psychopathology n=939	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age	38.85	13.19	40.11	13.17	40.09	13.06	41.74	13.20	33.12	10.93	40.57	13.16
	N	%	N	%	N	%	N	%	N	%	N	%
Gender												
Male	660	54.46%	1562	54.44%	1518	51.65%	84	55.63%	86	51.81%	449	47.82%
Female	552	45.54%	1307	45.56%	1421	48.35%	67	44.37%	80	48.19%	490	52.18%
Marital status												
Single	408	33.66%	903	31.47%	919	31.27%	48	31.79%	97	58.43%	286	30.46%
Married	804	66.34%	1966	68.53%	2020	68.73%	103	68.21%	69	41.57%	653	69.54%
Education												
Primary school	141	11.63%	320	11.15%	340	11.57%	21	13.91%	10	6.02%	117	12.46%
Secondary school	234	19.31%	562	19.59%	597	20.31%	33	21.85%	11	6.63%	195	20.77%
High school	438	36.14%	1156	40.29%	1141	38.82%	60	39.74%	45	27.11%	367	39.08%
Junior college	106	8.75%	233	8.12%	271	9.22%	15	9.93%	20	12.05%	73	7.77%
University	272	22.44%	527	18.37%	531	18.07%	20	13.25%	71	42.77%	163	17.36%
Graduate school	21	1.73%	71	2.47%	59	2.01%	2	1.32%	9	5.42%	24	2.56%
Perceived monthly income												
Low	132	10.89%	290	10.11%	329	11.19%	17	11.26%	21	12.65%	106	11.29%
Average	865	71.37%	2079	72.46%	2099	71.42%	111	73.51%	119	71.69%	654	69.65%
Upper	215	17.74%	500	17.43%	511	17.39%	23	15.23%	26	15.66%	179	19.06%
Chronic illness	98	8.09%	230	8.02%	255	8.68%	18	11.92%	19	11.45%	94	10.01%
Chronic illness among relatives	392	32.34%	820	28.58%	865	29.43%	45	29.80%	74	44.58%	289	30.78%

Differences in socio-demographic characteristics of latent classes are assessed by using 3-step regression analysis

Anxiety Group (n=151, 1.82%); 5) Negative Affect Group (n=166, 2.01%); and 6) General Psychopathology Group (n=939, 11.35%).

In addition to the findings regarding PHAM and latent classes, we identified that 46.38% of the Turkish sample reported poor sleep quality, 43.92% of the participants reported clinical levels of obsessive–compulsive symptoms, 10.8% had severe depressive symptoms and 13.34% had pathological levels of anxiety symptomatology in the national survey data. A series of studies examined the prevalence of psychiatric disorders occurred in different periods of the COVID-19 pandemic. At the awake of the breakout, in a community sample of 1210 individuals from 194 different cities in China, 53.8% of the participants were reported to be psychologically influenced by the pandemic, ranging from moderate to severe. Additionally, 28.8% of the participants revealed moderate to severe anxiety symptoms. Most serious fears were concerned with their family members that might be infected with the COVID-19 (75.2%) (Huang et al., 2020). Another research conducted immediately after the onset of the pandemic in a community population of 1060 individuals found that more than 70% of the participants showed serious psychological symptoms. The most common mental health problems were identified as obsessive–compulsive symptoms, phobic anxiety and psychotic symptoms, and high educated divorced or widowed elder people who were over the age of 50 were at greater risk for developing mental health problems (Tian et al., 2020). In another national survey in China among 55,657 participants reported that 53.8% of the sample experienced clinical depression, 46.7% experienced clinical anxiety, and 29.7% experienced clinical insomnia (Wang et al., 2021). Similarly, the prevalence rates of anxiety, depression, and comorbid anxiety-depression comorbidity were reported as much as 51.6%, 47.5%, and 24.5%, respectively (Wu et al., 2020). In consistent with the previous findings, our findings indicated that obsessive–compulsive symptoms, sleep disturbances and mood-realted probelems were prominent among community samples.

Pandemic Health Anxiety Structural Equation Model

The structural model of the current data showed that perceived vulnerability to diseases was directly associated with health anxiety, obsessive–compulsive symptoms, and sleep problems. Moreover, perceived vulnerability to diseases was indirectly linked to obsessive–compulsive symptoms and sleep problems through cyberchondria. Perceived vulnerability to diseases, which refers to one's attributions about the risk of contracting a disease, is considered to be as an integral part of the behavioral immune system. The concept of behavioral immune system includes recognizing the factors that might cause infection in the environment, activating cognitive and emotional processes in case of possible risk, and behaviors to avoid possible risk situations (Schaller & Park, 2011). The ability of the individual to properly evaluate the probability of exposure to potential infectious pathogens by optimal use of internal and external stimuli and to stay away from risky situations is an issue closely related to the optimal or sufficiently flexible use of the behavioral immune system. If this system is on fully alert, in other words, if it perceives the possibilities that will not cause trouble as risky, this situation may overshadow the benefits gained by the person (Schaller, 2015). On the other hand, individuals' negative evaluations related to their health status increase their fear of COVID-19 and lead individuals to be more careful about taking the necessary precautions against the risk of infection (Ahorsu et al., 2020). The results of a survey with a normal population sample of 7554 individuals in Brazil showed that individuals high in self-confidence and able to evaluate their vulnerability levels against diseases in a realistic way easily adapt to measures of outbreak; however, individuals who trusted the health system were more likely to reveal risky behaviors (Storopoli et al., 2020). In a similar vein, the literature consistently showed that perceived vulnerability to diseases and evaluations regarding the reliability of outbreak precautions significantly predicted compliance with outbreak rules and regulations (Clark et al., 2020; Makhanova & Shepherd, 2020; Prasetyo et al., 2020).

In a study conducted with a group of participants with psychiatric disorders in Taiwan, it was found that information related to infection, especially from the media, caused an increase in fear of COVID-19, which, in turn, increased depression, anxiety, and stress levels, then it reduced the personal sensitivity to measures to prevent infection (Chang et al., 2020). Especially during the outbreak, individuals who exposed to intensive information about infections and health issues were more likely to engage unduly search for the ways of staying healthy on the Internet (Zheng et al., 2020). In a study conducted in a general population sample of 1000 people over 50-year-olds in Iran, it was found that the negative cognitive evaluations of participants with respect to their physical health conditions increased their fear of COVID-19 that led to sleep problems which was significantly associated with other types of psychological problems (Ahorsu et al., 2020). Similarly, perceived vulnerability to diseases was significantly associated with COVID-19-related worries, social isolation, and traumatic stress (Boyraz et al., 2020).

During the outbreak, a host of online apps concerned with various life domains have been introduced; thus, the excessive use of Internet has brought behavioral risks such as cyberchondria along with its advantages (Király et al., 2020). It has been well-established that the lack of reliable information on health, the presence of many information that seems to be inconsistent with each other, and the lack of information that meets the need for relaxation and assurance on Internet may result in severe negative psychological outcomes, particularly during the outbreak (Starcevic et al., 2021). The present data supported these premises that perceived vulnerability to diseases significantly contributed to cyberchondria severity with a large effect size that indirectly led to increase in obsessive compulsive symptoms and poor sleep quality. Perceived vulnerability to diseases also was directly associated with health anxiety as well as obsessive–compulsive symptoms and poor sleep quality. More importantly, in the PHAM, cyberchondria revealed a robust association with poor sleep quality and obsessive–compulsive symptoms.

Although perceived vulnerability to diseases strongly contributed to the increase in cyberchondria severity, negative affect also played role in the emergence of health-related maladaptive behaviors on Internet. Indirect relationships of negative affect with obsessive compulsive symptoms and poor sleep quality were also mediated by cyberchondria. Negative affect seemed to be the strongest predictor of obsessive–compulsive symptoms in the PHAM. Besides, negative emotions directly predicted the deterioration in sleep quality. Fear of COVID-19 was the strong predictor of health anxiety. Moreover, indirect relationship between negative affect and health anxiety was mediated by fear of COVID-19. Our results were consistent with the preceding research studies addressing the pivotal role of affective problems in mental functioning. The results of a survey that was conducted in Bangladesh with 10.067 people showed that 33% of the participants experienced depression associated with COVID-19 and 5% developed suicidal thoughts due to outbreak (Mamun et al., 2021). In a study conducted with a large sample of American adults, it was found that after controlling for age, gender, educational level and ethnic group variables, and being caught with coronavirus, common anxiety symptoms, depression, loss of function, lack of social support and suicidal thoughts significantly increased COVID-19 anxiety (Lee et al., 2020). Another study, which was conducted in Turkey with individuals who were diagnosed with bipolar disorder and were in remission at the time of the study, revealed that the individuals' sleep quality substantially suffered during COVID-19 outbreak (Aydınoğlu & Yazla, 2021). In accordance with these findings, Asmundson et al. (2020) reported that individuals with anxiety-related disorders had higher levels of stress and fear associated with COVID-19 than individuals without any mental health problems.

Given the strong relationships converged on the structural model, it was identified that individuals with heightened affect regulation problems in terms of increased depression and anxiety were more vulnerable to obsessive compulsive symptoms and fear of COVID-19. Fear of COVID-19 was the robust predictor of health anxiety. Perceived vulnerability to diseases significantly contributed to cyberchondria. On the other hand, cyberchondria was significantly related to poor sleep quality.

Mixture Analysis of the Structural Model of Pandemic Health Anxiety

In the mixture analysis, maximum likelihood estimates computed in the PHAM were subjected to latent profile analysis. The six-latent-class was extracted as the optimal model in the analysis as follows: 1) Risk-Aversive Healthy Latent Class ($n = 1212$, 14.64%), 2) Incautious Healthy Latent Class ($n = 2869$, 34.67%), 3) Infection Obsessions Latent Class ($n = 2939$, 35.51%), 4) Health Anxiety Latent Class ($n = 151$, 1.82%), 5) Negative Affect Latent Class ($n = 166$, 2.01%), and 6) General Psychopathology Latent Class ($n = 939$, 11.35%). Both Risk-Aversive Healthy Latent Class and Incautious Healthy Latent Class was characterized by low levels of psychopathology. In sharp contrast to Incautious Healthy Latent Class, participants classified into Risk-Aversive Healthy Latent Class reported relatively greater scores on perceived vulnerability to diseases. Individuals allocated in the Infection Obsessions Latent Class were more likely to report severe levels of cyberchondria, fear of COVID-19, obsessive–compulsive symptoms, negative-affect, poor sleep quality. On the other hand, fear of COVID-19, health anxiety and perceived vulnerability to diseases were the hallmark of Health Anxiety Latent Class. Latent class membership probabilities of both Negative Affect Latent Class and General Psychopathology Latent Class were significantly connected to all psychological variables addressed in the study, whereas only obsessionality was not associated with Negative Affect Latent Class. More importantly, individuals in the Negative Affect Latent Class reported less severe levels of psychological problems than the General Psychopathology Latent Class. Most remarkably, participants in Negative Affect Latent Class differentiated from all other subgroups with greater chronic illnesses among their first-degree relatives, being younger and being more educated. It seems that individual differences of participants in the Negative Affect Latent Class from other latent classes represent a cohort effect which should be warranted in further studies. In line with our findings, Commodari and La Rosa (2020) identified that female adolescents who were living in red flagged zones in Italy were susceptible to experience severe psychological distress. Drastic changes in lifestyle due to lockdowns in terms of decreased levels of physical activity and reduced life-quality habits affected adults (Bivia-Roig et al., 2020), however, school closure probability multiplied the negative effects of COVID-19 among youngsters (Esposito et al., 2021).

Although a body of compelling evidence related to the psychological consequences of the COVID-19 pandemic has been emerged in the literature, there has been a paucity of research study using mixture analysis. Taylor et al. (2020a) argued that studies on COVID-19 generally reflect the fear of infection on a one-dimensional basis, whereas the stress caused by the pandemic should be addressed in five dimensions in the context of a syndrome approach: 1) Danger and contamination fears, 2) fears about economic consequences, 3) xenophobia, 4) compulsive checking and reassurance seeking, and 5) traumatic stress symptoms about COVID-19. The COVID-19 Stress Scales (Taylor et al., 2020b), which measure these five dimensions, were used to collect data from 6854 participants aged 18–94. The data subjected to latent profile analysis which classified the community sample in five latent profiles from the perspective of COVID-19 stress syndrome. It was observed that individuals grouped in the 1st and 2nd latent classes experienced a very low level of stress related to the pandemic process, and that 16% of the participants grouped into the 5th latent class experienced COVID-19 stress syndrome at the highest level. When the network analysis was performed among the five sub-dimensions measured, the danger of infection and the fear of getting sick were found to be at the center of all dimensions (Taylor et al., 2020a).

Given the evidence from the literature, the current data supported the previous findings that psychological profiles of the community samples in response to pandemic conditions significantly vary. Theoretical and empirical discussions on the subject include the heterogeneity of emotional responses caused by COVID-19 and suggest that the psychological aspects of COVID-19 should be handled in a multidimensional way as a syndrome (Asmundson & Taylor, 2020; Taylor et al., 2020a). However, the current national data from Turkey showed that perceived vulnerability to diseases, negative affect, fear of COVID-19, cyberchondria, health anxiety, obsessive–compulsive symptoms, and sleep quality appeared to be at the center of pandemic health anxiety. To the best of our opinion, the current data would be beneficial to promote effectiveness of public health measures, and health prevention and intervention programs concerned with the psychological strains that occur in community samples during the COVID-19 pandemic.

Limitations and Future Implications

This study has several drawbacks. First, the study design was cross-sectional that identified relationships between the addressed variables of interest could not be interpreted in a causality manner. These findings should be replicated in longitudinal design research, particularly using latent transition analysis. Second, the data collected online which may have resulted in participant selection bias. Third, self-report measures were used in data collection process which conveys subjectivity of assessments to an extent. Forth, online photovoice research strategy provides a wealth avenue to collect in-depth information about psychological facts, particularly psychological consequences of COVID-19 (Tanhan, 2020; Tanhan & Strack, 2020; Tanhan et al., 2021). The variables of interest that were addressed in the current data should be handled using photovoice technique in future studies. In spite of these limitations, the current data provides an extensive assessment for psychological aspects of pandemic psychology in a relatively large and representative community sample.

Present study has several clinical implications. At first, the PHAM shows that health anxiety, obsessive–compulsive symptoms and sleep problems vary depending on the cognitive evaluations and emotion regulation capacities of individuals, especially during the pandemic period. In this sense, it is thought that cognitive-behavioral approaches can be used when designing social mental health-enhancing and protective intervention programs in the normal population, especially during the pandemic period, and it is important to include emotion regulation skills in these programs.

Moreover, the increasing fears of COVID-19 due to the increase in negative affect strongly predicted health concerns. Health concerns and fear of COVID-19 represent a separate dimension among the variables addressed. Therefore, it is understood that protective intervention programs regarding the fear of COVID-19, health anxiety, cyberchondria, and obsessive–compulsive symptoms should primarily focus on emotion regulation skills. Thirdly, during the pandemic period, deterioration in sleep quality was found to be associated with increased severity of cyberchondria due to perceived vulnerability to diseases. Thus, it is beneficial to address sleep problems through interventions focusing on cognitive-behavioral underlying mechanism of cyberchondria.

Lastly, this study indicated that there is a heterogeneity in the Turkish population in terms of the PHAM variables, which means that the psychological problems arising from COVID-19 should be handled with multidimensional and multilevel approach. For instance, it can be suggested that preventive interventions may be beneficial for the Risk-Aversive Healthy Group to maintain their conditions. Moreover, interventions focusing more on emotion regulation skills, anxiety management skills and increasing sleep hygiene may be more appropriate for the Infection Obsessions Group and Health Anxiety Group. On the other hand, individuals in General Psychopathology and Negative Affect groups scored extremely high in terms of the variables considered in both groups. Therefore, it can be said that these individuals represent more clinical groups and may need a more intense clinical intervention. In a nutshell, it can be beneficial that health prevention and intervention programs consider the inter-class differentiation.

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Code Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical Approval All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2000 (5). Informed consent was obtained from all participants for being included in the study.

Conflict of Interest All authors declare there is no conflict of interest.

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