Health anxiety and information-seeking in the digital age: a two-wave study of cyberchondria

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Abstract

Purpose – Cyberchondria, characterized by excessive online health information seeking and resulting anxiety, is intensifying. This study examines how threat perceptions and cognitive factors drive cyberchondria and how this condition leads to health information fatigue on social media (HIFSM), self-medication, and therapy compliance.

Design/method/approach – This study integrates protection motivation theory (PMT), cognitive load theory (CLT), and stressor-strain-outcome (SSO) model to inform the partial least squares path modeling (PLSPM) of a two-wave survey over six months of 400 participants.

Findings – Perceived susceptibility, perceived severity, online information trust, and information overload intensify cyberchondria, which sparks HIFSM, and in turn, increases self-medication while undermining therapy compliance. Trust in physicians mitigates these adverse effects.

Practical implications – Since information overload fuels cyberchondria, the findings urge social media developers to help curb cyberchondria by prioritizing credible health content, integrating source-verification features, and collaborating with clinicians to curate guideline-based information.

Originality – This study advances cyberchondria research by uniting three theoretical perspectives and identifying physician trust as a protective factor.

Keywords – Cyberchondria; Protection motivation theory; Cognitive load theory; Stressor-strain-outcome model.

1. Introduction

Digital advances have transformed how people seek health information (Sahoo *et al*., 2023). Once confined to structured, expert-moderated communities (Lambert and Loiselle, 2007), medical discussion now thrives on social media (Zhao and Zhang, 2017). Platforms such as Facebook, Instagram, TikTok, and YouTube expose users to health content both actively and passively through algorithm-driven feeds (Oeldorf-Hirsch and Neubaum, 2025; Riaz *et al*., 2023). This blending of advice with advertisements, entertainment, and personal narratives hampers users' ability to gauge credibility (Hajli et al., 2022). Reliance on social media for both news and health information is also growing among digital natives, merging current-affairs consumption with self-directed health seeking (Wakefield and Wakefield, 2024).

In this context, cyberchondria, characterized by excessive online health searches that escalate anxiety, poses a pressing concern (Starcevic and Berle, 2013). The COVID-19 pandemic magnified this phenomenon as individuals confronted uncertainty over symptoms and transmission (Lim, 2021; Zheng *et al*., 2021a). Social media became the go-to source for instant updates and reassurance, yet that very reliance intensified cyberchondria (Zheng *et al*., 2023). The quest for clarity often led users into a deluge of both reliable and false information (Vismara *et al*., 2022), undermining their ability to judge accuracy and fueling anxiety and doubt (McMullan *et al*., 2019). Compulsive engagement with inconsistent, unverifiable content, driven by a desperate search for reassurance, paradoxically heightens distress, invites misdiagnosis, and erodes trust in medical professionals (Laato *et al*., 2020b). Rising self-diagnosis, spurred by lengthy doctor wait times (The Guardian, 2023) and widespread social media queries (Statista, 2023), further exposes users to misinformation (Lim, 2023) and inappropriate self-treatment (Laato *et al*., 2020).

Though the World Health Organization (2025) lifted its global emergency designation in May 2023, SARS-CoV-2 continues to circulate at significant levels, prompting biannual risk assessments and regional alerts when cases spike (UK Health Security Agency, 2025). Seasonal influenza and other respiratory pathogens remain endemic. For instance, Scotland's deadliest flu season of the century struck in early 2025, claiming 168 lives in one week and triggering urgent public health measures (The Times, 2025). These trends demonstrate that viral threats persist beyond formal emergencies. Assessing cyberchondria's antecedents and outcomes is thus essential to protect mental wellbeing and ensure digital health tools guide, rather than mislead, users (Riaz *et al*., 2023; Vismara *et al*., 2022).

Against this backdrop, this article proposes a conceptual model to clarify how cyberchondria shapes health decisions. Grounded in a systematic review following the SPAR-4-SLR protocol (Paul *et al*., 2021; Appendices A and B), the model integrates protection motivation theory (PMT), cognitive load theory (CLT), and the stressor-strain-outcome (SSO) model. Prior studies have examined psychological, behavioral, and environmental contributors to cyberchondria (Hashemi *et al*., 2020; Jeong *et al*., 2023; Laato *et al*., 2020a; Zheng *et al*., 2023), but three *gaps* remain.

First, research on cyberchondria predictors focuses almost exclusively on pandemic-related anxiety (Ahorsu *et al*., 2022; Honora *et al*., 2022; Jeong *et al*., 2023), overlooking enduring drivers such as social media's algorithmic amplification of health content (Oeldorf-Hirsch and Neubaum, 2025) and the persistent uncertainty of everyday illness (Brown et al., 2020). Studies also apply theoretical frameworks in isolation, for instance, CLT and stimulus-organism-response (SOR) model highlight digital overload (Laato *et al*., 2020; Zheng *et al*., 2022) while the health belief model addresses protective responses (Honora *et al*., 2022; Zheng *et al*., 2021a). This article bridges those perspectives, uniting motivational insights from PMT (Rogers, 1975) with CLT (Sweller, 2011) to explain how threat perceptions and cognitive factors drive cyberchondria on social media.

Second, existing work treats psychological distress and behavioral outcomes separately, leaving a gap in understanding how anxiety translates into actions such as vaccine hesitancy or therapy non-compliance (Shahani *et al*., 2023; Zheng *et al*., 2021b). Drawing on the SSO model (Koeske and Koeske, 1993), this article positions health information fatigue on social media (HIFSM) as the key strain (Pang, 2024) that links

cyberchondria stressors to self-medication and therapy compliance (Kivelevitch *et al*., 2012). This framing clarifies how personal risk perceptions, information trust, and overload combine to shape health behaviors (Laato *et al*., 2020b; Zheng *et al*., 2023).

Third, few studies examine coping resources that buffer cyberchondria's impact. Trust in physicians may reduce reliance on unverified online information and ease health-related uncertainty (Deniz *et al*., 2021; McMullan *et al*., 2019). This article tests trust in physicians as a moderator of the fatigue–behavior link. Employing a two-wave survey design offers stronger causal insights into both antecedents (perceived susceptibility, perceived severity, online information trust, and information overload) and consequences (HIFSM, self-medication, and therapy compliance) of cyberchondria and guides strategies to steer digital health tools toward supporting user wellbeing.

To address these gaps, this article proposes three research questions (RQs):

RQ1. How do threat perceptions (perceived susceptibility and perceived severity) and cognitive factors (online information trust and information overload) drive cyberchondria on social media?

RQ2. How does cyberchondria act as a stressor that generates HIFSM and how does that fatigue influence self-medication and therapy compliance?

RQ3. To what extent does trust in physicians buffer the effects of cyberchondria and HIFSM on these health behaviors?

This article makes three contributions. First, this article integrates PMT, CLT, and the SSO model to overcome the blind spots of each when used alone (i.e., PMT omits cognitive overload, CLT ignores motivational drivers, SSO lacks clear antecedents) (*what*), thereby offering a unified view of how threat appraisals and information-processing demands converge in algorithm-driven social feeds—a dynamic absent from alternative platforms such as expert-moderated forums (*so what*). Second, this article sharpens construct boundaries by treating information overload as a cognitive trigger and HIFSM as the ensuing strain, then mapping how that sequence drives self-medication and therapy compliance in the context of HIFSM (*what*)—where unmoderated, algorithm-driven feeds magnify both volume and variability of high-stakes health information, setting it apart from static, expert-vetted content of official health portals (*so what*). Third, this article uncovers that trust in physicians weakens both the direct effects of cyberchondria and the indirect effects via HIFSM on self-medication and therapy non-compliance (*what*), thereby pointing to a concrete strategy for healthcare providers to counteract digital-age health anxieties and curb maladaptive health behaviors (*so what*).

The remainder of this article proceeds as follows. Section 2 reviews relevant theories. Section 3 develops the conceptual model and hypotheses. Sections 4 and 5 present the methodology and results. Section 6 discusses theoretical and practical implications, acknowledges limitations, and suggests avenues for future research.

2. Theoretical background

Cyberchondria studies concentrate on coping with health threats (Fu *et al*., 2023; Jeong *et al*., 2023; Soroya *et al*., 2021), medical decision-making (Khan and Pandey, 2022; Laato *et al*., 2020a), and preventive behavior (Hashemi *et al*., 2020; Shahani *et al*., 2023; Wakefield and Wakefield, 2024). Most of this work, however, treats information seeking as a generic activity, neglecting the specific goals that drive a search (Zimmerman and Shaw, 2020). Evidence is likewise drawn mainly from medical websites or online communities (Lambert and Loiselle, 2007), even though social platforms differ sharply in interactivity, speed, and source credibility (Lin *et al*., 2016; Zhao and Zhang, 2017). For example, Facebook leverages peer endorsement to build trust, whereas Twitter's (X's) rapid, unfiltered posts heighten overload (Alhavan et al., 2023). These platform-specific dynamics thus demand fresh scrutiny (Fontes-Perryman and Spina, 2022; Honora *et al*., 2022).

Key constructs such as trust (Khan and Pandey, 2022), information overload (Laato *et al*., 2020a;

Zheng *et al*., 2023), and psychological strain (Zheng *et al*., 2021) have been analyzed, yet almost always in isolation. Cross-sectional designs dominate (Zheng *et al*., 2021), obscuring causal pathways, and trust in physicians is typically treated as a direct predictor (Khan and Pandey, 2022), rather than a buffer against strain. Addressing these gaps requires a framework that unites motivational forces, cognitive limits, and stress processes while recognizing the rapid, algorithm-driven flow of social media content, especially in health information seeking, where misguided advice can prompt hazardous self-diagnosis, unsafe treatment choices and, in extreme cases, life-threatening outcomes.

PMT explains how perceived severity and susceptibility prompt defensive actions (Farooq *et al*., 2020), but the theory overlooks mental overload triggered by dense online content (Laato *et al*., 2020b). CLT clarifies how excessive information and source doubts impair judgment (Sweller, 2011), yet offers little guidance on the downstream emotional and behavioral fallout. The SSO model fills that gap, tracing the path from stressors to psychological strain and, finally, to behavior (Duong *et al*., 2025; Kivelevitch *et al*., 2012; Pang, 2024). Integrating PMT, CLT, and the SSO model captures threat appraisals, information-processing demands, and emotional strain in a single sequence. Figure 1 positions perceived susceptibility and severity (PMT) and online information trust and information overload (CLT) as antecedents of cyberchondria, the focal stressor; identifies HIFSM as the ensuing strain; and links that strain to self-medication and therapy compliance (SSO) while testing physician trust as a moderating resource.

[Insert Figure 1]

2.1 Protection motivation theory (PMT)

PMT distinguishes *coping appraisal* (e.g., evaluations of self-efficacy, response efficacy, response costs) from *threat appraisal*, which centers on *perceived severity* (e.g., beliefs about the seriousness of a health hazard) and *perceived susceptibility* (e.g., beliefs about personal vulnerability) (Rogers, 1975). This article focuses on threat appraisal because judgments of severity and susceptibility directly drive the motivation to seek health information online.

Perceived severity reflects expectations of potential harm while *perceived susceptibility* captures one's perceived risk of encountering that harm (Laato *et al*., 2020b; Ling *et al*., 2019). PMT research shows that higher severity and susceptibility heighten protective intentions, yet in social media environments, these appraisals can also fuel anxiety and compulsive searching (Farooq et al., 2020; van Bavel *et al*., 2019)—defining features of cyberchondria (Starcevic and Berle, 2013). Hence, applying PMT to online health contexts clarifies how threat perceptions, amplified by social feeds, underpin excessive information seeking and its downstream effects.

2.2 Cognitive load theory

CLT emphasizes the limits of working memory and the risk of overload when individuals face excessive information (Sweller, 2011). This theory distinguishes intrinsic load (the complexity inherent in content) from extraneous load (the inefficiency of its presentation) and germane load (the effort devoted to integrating new information into existing schemas) (Yin *et al*., 2018). When these combined demands exceed capacity, users cannot process or retain information effectively.

Although CLT originated in instructional design (Paas and van Merriënboer, 2020; van Merriënboer and Ayres, 2005), its principles apply to digital contexts. On social media, unfiltered streams of advertisements, posts, and personal stories generate *information overload* through sheer volume, ambiguity, and inconsistency (Zheng *et al*., 2023). Low *online information trust* compounds that strain, as when credibility is uncertain, users either accept misinformation or hesitate to act, outcomes that undermine sound decision-making (Keselman *et al*., 2019; Swar *et al*., 2017). This article, therefore, focuses on information overload and online information trust as the principal cognitive antecedents of cyberchondria, as isolating these factors clarifies how social media's unmoderated, algorithm-driven content disrupts users' cognitive equilibrium and fuels maladaptive health behaviors.

2.3 Stressor-strain-outcome (SSO) model

The SSO model, first developed to explain workplace stress (Koeske and Koeske, 1993), holds that certain conditions or behaviors act as stressors, which induce psychological strain and, in turn, shape outcomes. In organizational contexts, problematic Internet and social media use have been identified as stressors that trigger emotional exhaustion and disengagement (Cao and Sun, 2018; Cao *et al*., 2018). Recent extensions apply this logic to digital interactions more broadly, showing how excessive online engagement breeds fatigue and maladaptive responses (Duong *et al*., 2025; Pang, 2024).

This article adapts the SSO model to cyberchondria on social media by treating excessive health-information searches as the stressor. That stressor exposes users to conflicting, high-volume content, which generates HIFSM—a form of emotional exhaustion and weariness from relentless exposure to health posts (Pang, 2024). Consistent with Doorman and Zapf (2004), stressors are attributes or behaviors linked to psychological strain, wherein strain mediates the link between stressors and outcomes (Um and Harrison, 1998). In our model, HIFSM bridges cyberchondria and two behavioral outcomes (self-medication and therapy compliance), illustrating how digital-induced fatigue translates into tangible health decisions (Zhang *et al*., 2022).

3. Hypotheses development

3.1 Perceived susceptibility, perceived severity, and cyberchondria

PMT argues that threat appraisal hinges on two judgments: perceived susceptibility (the likelihood of personal harm) and perceived severity (the gravity of that harm) (Rogers, 1975). Higher scores on either dimension intensify coping efforts, often through information seeking (Starcevic and Berle, 2013; White and Horvitz, 2009). During infectious-disease outbreaks, elevated susceptibility and severity beliefs have spurred heavy social-media use for pandemic updates (Husnayain *et al*., 2020) and for everyday illnesses such as seasonal flu (Ling *et al*., 2019). Repeated exposure to contradictory posts can, however, heighten anxiety and ignite cyberchondria—a pattern observed in studies of COVID-19, H1N1, and other health crises (Fu *et al*., 2023; Laato *et al*., 2020b). Therefore, threat appraisals of higher perceived susceptibility and severity should predict stronger cyberchondria:

H1. Perceived susceptibility positively influences cyberchondria.

H2. Perceived severity positively influences cyberchondria.

3.2 Online information trust, information overload, and cyberchondria

Social media remains the primary channel for sharing public health news, personal experiences, and health advice (Ahorsu *et al*., 2022; Riaz *et al*., 2023). Frequent exposure fosters confidence in what users read, yet that confidence often replaces careful source evaluation (Zheng et al., 2023). When unverified posts are taken at face value, misinformation spreads (Lim, 2023) and cognitive shortcuts replace critical appraisal (Laato *et al*., 2020b), conditions that heighten anxiety and sustain repeated symptom searches—key hallmarks of cyberchondria (Baumgartner and Hartmann, 2011). This pattern aligns with CLT and underscores that online information trust operates as a metacognitive checkpoint, guiding which content users process and how they allocate their limited cognitive resources.

Concurrently, social feeds bombard users with a variety and volume of health content that easily outstrips working-memory capacity (Farooq *et al*., 2020). Consistent with CLT (Sweller, 2011), information overload strains working memory, depletes mental resources, increases uncertainty, and leads individuals into compulsive and repeated searching to reduce doubt (Brown *et al*., 2020; Keselman *et al*., 2019). The resulting feedback loop of search, overload, anxiety, and further search thus intensifies cyberchondria (Eastin and Gunisler, 2006; Zheng and Jiang, 2022). Therefore, information-processing demands from higher online information trust and greater information overload should predict stronger cyberchondria:

H3. Online information trust positively influences cyberchondria.

H4. Information overload positively influences cyberchondria.

3.3 Consequences of cyberchondria

Cyberchondria's compulsive searches heighten health anxiety, functioning as an environmental stressor that can spark irrational actions (Fu *et al*., 2023; Khan and Pandey, 2022; Starcevic *et al*., 2020; Yan *et al*., 2021; Yang *et al*., 2021), including unnecessary doctor visits and impulsive online drug purchases (Eichenberg and Schott, 2019).

The resulting strain extends beyond momentary worry. An endless stream of often conflicting posts overwhelms working-memory limits (Soroya *et al*., 2021), feeds uncertainty (Swar *et al*., 2017), and drives HIFSM (Ashiru *et al*., 2023; Cao *et a*l., 2019; Zheng *et al*., 2023). Some users retreat into avoidance (Soroya *et al*., 2021), while others intensify the search and deepen fatigue and distress (Ashiru *et al*., 2023).

PMT suggests that heightened threat appraisal should encourage protective behavior, yet cyberchondria's relentless information gathering can undermine perceived control. To regain agency, individuals may self-medicate rather than consult professionals (Rajamma *et al*., 2021; Starcevic *et al*., 2020). Excessive searching also seeds doubt about medical advice, eroding therapy compliance despite the potential benefits of being an informed patient (Prigge *et al*., 2015; Starcevic *et al*., 2019). Therefore, consistent with PMT's protective-behavior logic and the SSO model's depletion effects, the anxiety-driven, compulsive searches of cyberchondria, as a stressor, should increase individuals' propensity to self-medicate, exacerbate HIFSM, and undermine therapy compliance:

H5a. Cyberchondria positively influences propensity to self-medicate.

H5b. Cyberchondria positively influences HIFSM.

H5c. Cyberchondria negatively influences therapy compliance.

3.4 HIFSM and decision-making

HIFSM is defined as emotional exhaustion and motivational disengagement triggered by sustained exposure to health advertisements, posts, and personal stories on social media (Lee *et al*., 2016; Whelan *et al*., 2020). As cognitive and affective resources deplete, users' capacity to appraise, filter, and store relevant content falls, reducing information efficacy—the confidence with which they can apply what they learn (Jiang, 2022).

This depletion has two compounding effects. First, vigilance drops, where fact-checking and source comparison give way to heuristics and shortcuts, inviting uptake of unverified advice (Park, 2019), as exhausted users, seeking quick relief, may self-medicate with over-the-counter drugs or supplements sourced from the very platforms that fatigued them. Second, fatigue corrodes trust in professional guidance, as repeated exposure to contradictory posts fosters skepticism toward public health messages, weakening adherence to prescribed regimens (Fontes-Perryman and Spina, 2022; Riaz *et al*., 2023). Therefore, the emotional strain of HIFSM is expected to push individuals toward risky autonomy while pulling them away from evidence-based care:

H6a. HIFSM positively influences the propensity to self-medicate.

H6b. HIFSM negatively influences therapy compliance.

3.5 Mediation role of HIFSM

Applying the SSO model, cyberchondria operates as the stressor and HIFSM represents the ensuing strain

(Baj-Rogowska, 2023; Cao and Sun, 2018), which may manifest a state of emotional exhaustion and cognitive saturation produced by endless scrolling through symptom posts, personal narratives, and competing advice (Fox and Moreland, 2015; Zhao *et al*., 2021). This fatigue saps mental energy, dulls motivation to evaluate new material, and leaves users feeling overwhelmed (Ou *et al*., 2023; Pang *et al*., 2022).

Strain of this kind skews decision processes. Anxious individuals often pursue quick fixes to restore a sense of control, turning to over-the-counter remedies or online vendors rather than consulting professionals—behavior repeatedly linked to cyberchondria (Elayeh e*t al*., 2021; Vannucci *et al*., 2017). Traditional psychology shows that anxiety narrows attention, distorts threat appraisal, and promotes heuristic thinking, all of which heighten self-medication risk (Khan and Pandey, 2022).

HIFSM also erodes trust in medical guidance. Coping theories suggest that, when strain becomes intolerable, people disengage from the very information sources that cause their stress (Dhir *et al*., 2018; Oldham and Kleiner, 1990; Pang, 2024). Such disengagement can manifest as skepticism toward physicians, missed appointments, or selective adherence to prescriptions, thereby undermining therapy compliance. Therefore:

H7a. HIFSM mediates the relationship between cyberchondria and propensity to self-medicate.

H7b. HIFSM mediates the relationship between cyberchondria and therapy compliance.

3.6 Moderation role of trust in physicians

Trust anchors the patient-physician relationship and remains a decisive predictor of satisfaction, persistence with medication, and overall treatment success (Lehane and McCarthy, 2007). High trust not only bolsters adherence but also shields patients from health-resistant behaviors, as individuals who believe in their physician's competence and intent are less inclined to self-medicate and more willing to follow professional guidance (Bonti, 2017; Gabay, 2015; Lee and Lin, 2009).

This protective effect extends to digital contexts. Strong physician trust reduces the temptation to act on unverified remedies encountered online and dampens doubts about prescribed regimens (Bauer *et al*., 2014; Sandhofer *et al*., 2017). Such trust also fosters a collaborative stance in which patients consult their clinicians before adjusting or abandoning treatments suggested on social media (Fereidouni *et al*., 2019; Lee *et al*., 2013). Trust, therefore, functions as a psychological buffer that can dilute the anxiety, confusion, and impulsivity generated by cyberchondria and HIFSM.

H8a. Trust in physicians weakens the positive relationship between cyberchondria and self-medication.

H8b. Trust in physicians weakens the positive relationship between HIFSM and self-medication.

H8c. Trust in physicians weakens the negative relationship between HIFSM and therapy compliance.

H8d. Trust in physicians weakens the negative relationship between cyberchondria and therapy compliance.

4. Method

A two-wave panel survey captured the temporal dynamics among all study variables. Appendix C provides full methodological details while the essentials are illustrated in Figure 2 and summarized below.

All constructs were measured using established seven-point Likert scales adapted from prior literature, with minor modifications for the present context (Appendix D). The UK offered an ecologically valid setting as nearly two-fifths of its social media users, especially millennials, consult platforms, such as Facebook, Instagram, Snapchat, LinkedIn, and Twitter (X) (Alhavan *et al*., 2023), for symptom advice before visiting

clinicians (Naslund *et al*., 2020). Purposive sampling targeted that cohort. Screening ensured respondents were millennials (born in 1981 to 1996), had searched health content on social media at least twice in the prior two months, and reported no severe medical diagnoses. Wave 1 (August 1 to September 30, 2023) recorded threat appraisals (perceived susceptibility and severity), information-processing demands (online information trust and information overload), and cyberchondria. Wave 2 (January 1 to February 29, 2024) captured HIFSM, trust in physicians, and behavioral outcomes (self-medication and therapy compliance). Three months between waves balanced recall accuracy with sufficient temporal separation for causal inference. Of 600 invitations, 500 completed Wave 1; 410 returned at Wave 2. Ten straight-lined cases were removed, yielding 400 matched observations.

[Insert Figure 2]

5. Results

5.1 Participant profile

The demographic breakdown of respondents (Table 1) revealed a majority being female (64.5%), predominantly aged between 27 to 34 years (63.8%), with the largest educational group holding a bachelor's degree (65.8%). Most respondents lived in shared apartments or houses (50.0%), reported spending 4 to 6 hours on social media daily (40.5%), and registered Twitter (X) as their primary platform for seeking health information (32.4%). The frequency of searching for health information was mostly occasional (42.5%), with a significant focus on mental health topics (13.6%), depression (11.4%), and access to healthcare (11.2%).

[Insert Table 1]

5.2 Preliminary checks

To assess data quality, both common method bias (CMB) and non-response bias were examined. CMB was tested using Harman's single-factor test and the marker variable test (Lindell & Whitney, 2001). The largest variance explained by a single factor was 38.827% (<50%), and correlations between the marker variable (social desirability) and study constructs were low (<0.03) and non-significant (p>0.05), indicating minimal CMB (MacKenzie & Podsakoff, 2012). Non-response bias was evaluated by comparing early and late respondents (Armstrong & Overton, 1977). Chi-square tests showed no significant differences (p>0.05) across demographic variables, confirming the absence of non-response bias. Collectively, these results affirm that neither CMB nor non-response bias threatens the study's validity (Appendix E).

5.3 Measurement model

This study assessed the constructs for convergent and discriminant validity alongside internal consistency (reliability) to ensure the robustness of the measurement model.

Convergent validity and internal consistency (reliability) were first established. All item loadings surpassed the minimum threshold of 0.708 (Table 2), indicating a strong association with their respective constructs (Hair *et al*., 2022). The composite reliability for each construct exceeded the minimum benchmark of 0.70 and the average variances extracted were above the 0.50 threshold, suggesting that the constructs possess a satisfactory level of internal consistency and that a significant proportion of the variance in the items can be attributed to their associated constructs.

[Insert Table 2]

Discriminant validity, which assesses the extent to which a construct is distinct from other constructs within the model, was also confirmed. According to Fornell and Larcker's (1981) criterion, the square root of average variance extracted for each construct was higher than the correlations between that construct and all others, indicating that each construct shares more variance with its indicators than with those of other

constructs (Table 3). Additionally, the heterotrait-monotrait (HTMT) ratio for all construct comparisons fell below the 0.85 threshold (Henseler *et al*., 2015), further substantiating the discriminant validity of the constructs.

[Insert Table 3]

5.4 Structural model

In the assessment of the structural model, the study first addressed potential autocorrelation issues due to the utilization of time-lagged data, employing the Durbin-Watson (D-W) test as recommended by Watson and Durbin (1951). The results indicated no significant autocorrelation within the dataset (Table 4), with D-W values closely approximating the optimal value of 2.0, thereby affirming the independence of the residuals in the time series data.

Subsequent analysis focused on the hypothesized relationships within the model. To address RQ1, the findings from wave 1 demonstrated that perceived susceptibility (H1: β=0.175, p<0.01), perceived severity (H2: β=0.121, p<0.01), online information trust (H3: β=0.199, p<0.01), and information overload (H4: β=0.502, p<0.01) all positively influenced cyberchondria, thereby supporting H1–H4. The variance explained in cyberchondria by these predictors was substantial at 60.3%. It is noteworthy that control variables such as age, gender, education level, and frequency of health information search did not exhibit significant relationships with cyberchondria, whereas social media-health literacy showed a positive association (β=0.120, p<0.05).

The next analyses revealed a significant positive relationship between cyberchondria and both the propensity to self-medicate (β=0.447, p<0.01) and HIFSM (β=0.675, p<0.01), supporting H5a and H5b. Another significant positive relationship was found between HIFSM and the propensity to self-medicate (β=0.132, p<0.05), supporting H6a. Conversely, cyberchondria (β=-0.120, p<0.05) and HIFSM (β=-0.125, p<0.05) were found to negatively impact therapy compliance, supporting H5c and H6b. These relationships demonstrated explanatory powers ranging from 33.6% to 45.6%, after accounting for non-significant control variables.

In response to RQ2, the mediation analysis underscored the pivotal role of HIFSM, specifically, HIFSM significantly mediated the relationship between cyberchondria and the propensity to self-medicate (β=0.089, p<0.05), as well as between cyberchondria and therapy compliance (β=-0.084, p<0.05), supporting H7a and H7b. These findings highlight the integral role of HIFSM as a mediator in the pathways linking cyberchondria to critical health-related decision-making processes.

To answer RQ3, the study utilized a two-stage approach (Becker *et al*., 2023) to test whether trust in physicians moderates the effects of cyberchondria and HIFSM on health-related behaviors. The results in Table 4 revealed significant moderating effects of trust in physicians on the relationships between HIFSM and therapy compliance (β=-0.151, p<0.01), as well as between cyberchondria and therapy compliance (β=-0.145, p<0.01), supporting H8c and H8d. The effect sizes for these moderation effects were quantified as small, underscoring the nuanced yet impactful role of trust in healthcare providers in these dynamics. Conversely, trust in physicians did not significantly moderate the relationships between cyberchondria and the propensity to self-medicate (β=-0.010, p=0.381>0.05) or between HIFSM and the propensity to self-medicate (β=0.016, p=0.321>0.05), indicating that H8a and H8b were not supported.[1] The interaction plots further illustrated these findings, showing a discernible difference in the gradient of the lines representing high and low trust in physicians. Specifically, higher trust in physicians was associated with a mitigation of the negative impacts of cyberchondria and HIFSM on therapy compliance, as depicted in Figure 3 Panel A

[1] In order to verify the robustness of our structural model findings, a series of supplementary analyses were conducted, incorporating nonlinearity, endogeneity, and unobserved heterogeneity (Sarstedt *et al*., 2020) (Tables F1 to F3 in Appendix F).

and Panel B.

[Insert Figure 3]

The study also assessed the predictive relevance of the model through the $PLS_{predict}$ procedure, a method that evaluates the out-of-sample prediction capability of PLSPM models (Shmueli *et al*., 2019). The $Q^2_{predict}$ values for all endogenous constructs were found to be greater than 0 (Table 4), thereby affirming the model's ability to offer meaningful predictions regarding the constructs of interest.

[Insert Table 4]

6. Discussion, implications and conclusion

6.1 Discussion

This article examined how threat, cognitive, and emotional appraisals interact within social-media feeds to shape self-medication and therapy compliance. The model, grounded in PMT, CLT, and the SSO model, received support for 13 of 15 hypotheses, offering a fresh perspective on anxiety-driven health searches and their behavioral fallout.

6.1.1 Antecedents of cyberchondria

Perceived susceptibility, perceived severity, online information trust, and information overload all intensify cyberchondria (H1–H4). These results align with prior work linking threat and cognitive appraisals to anxiety-driven searches (Laato *et al*., 2020a; Ling *et al*., 2019; Zheng *et al*., 2023). Information overload produced the largest impact, highlighting the influence of cognitive burden. Earlier research shows that excessive, conflicting content overloads working memory and impairs critical evaluation (Sweller, 2011; Laato *et al*., 2020b). The present results confirm that the sheer volume and uncertain credibility of social-media posts magnify stress, even outside a pandemic context, suggesting that information-processing demands remain potent in routine health concerns. Yet, higher online information trust counters this overload by directing attention toward more reliable sources, thereby effectively conserving working-memory capacity and reducing anxiety, consistent with CLT's emphasis on optimized cognitive load (Sweller, 2011). These findings, in turn, clarify how threat appraisals and information-processing demands jointly shape cyberchondria, positively and negatively, pointing to the need for platforms and users to cultivate credible signals that alleviate cognitive burden.

6.1.2 Consequences of cyberchondria

Cyberchondria increases HIFSM (H5b) and both raise the propensity to self-medicate while lowering therapy compliance (H5a, H5c, H6a, and H6b). The mediation tests reveal that HIFSM conveys the effects of cyberchondria to both health behaviors (H7a, H7b). These findings extend earlier research that linked online exposure to anxiety and mental fatigue (Ashiru *et al*., 2023; Cao e*t al*., 2019), and while prior studies framed self-medication largely as a cost-saving strategy (Ayalew, 2017; Ruiz, 2010), the results of the present study indicate an affect-laden, cognitively strained pathway in which overwhelmed users bypass professional care for quick, self-directed remedies (Fontes-Perryman and Spina, 2022; Jiang, 2022; Park, 2019). Similarly, previous studies sometimes proposed that cyberchondria prompts greater medical engagement (Singh *et al*., 2016), however, the results presented herein reveal the opposite—that is, when cyberchondria coincides with HIFSM, confusion and frustration appear to erode confidence in clinicians, discouraging adherence.

6.1.3 Efficacy of trust in physicians as a solution

Trust in physicians did not weaken the links from cyberchondria or HIFSM to self-medication (rejecting H8a and H8b). Earlier evidence shows that strong trust usually curtails risky self-medication

(Khan and Pandey, 2022) and thus the divergence in the present study may reflect contextual factors such as cultural norms that prize autonomy or the ready availability of over-the-counter treatments (Machado-Alba *et al*., 2014; Peng *et al*., 2020; Wu *et al*., 2022). In contrast, trust reduced the negative impact of both cyberchondria and HIFSM on therapy compliance (support for H8c, H8d). Notably, while prior research has treated trust mainly as a direct antecedent of compliance (Erdem and Harrison-Walker, 2006; Lee and Lin, 2009), the present evidence positions trust as a protective moderator or safeguard that buffers anxiety-laden fatigue, mitigating the slide from digital distress to non-adherence, or in other words, preserving adherence even when users feel overwhelmed.

6.2 Theoretical implications

This study advances theory in three major ways, namely, (1) combining PLT and CLT to explain cyberchondria's triggers, (2) extending the SSO model with HIFSM as a strain, and (3) establishing trust in physicians as a boundary condition.

Firstly, this study highlights that threat appraisal (perceived susceptibility and severity) and information-processing demands (online information trust and information overload) rarely appear in a single model, yet the current evidence shows that their joint presence powerfully predicts cyberchondria. Information overload produced the largest path coefficient, confirming CLT's contention that excessive, poorly curated content overwhelms working memory and heightens anxiety (Sweller, 2011). At the same time, high threat appraisal, central to PMT, intensifies the urgency to search (Rogers, 1975). When these conditions converge on social media, a feedback loop forms, where users feel vulnerable, confront an avalanche of posts, and spiral into compulsive searches. Integrating the two theories, therefore, supplies a comprehensive lens that explains why cyberchondria flourishes in settings where volume, variability, and personal relevance of content fluctuate hourly (Hajli *et al*., 2022; Laato *et al*., 2020b). In turn, future studies can build on this framework to test additional cognitive or motivational drivers without fragmenting the explanatory logic.

Secondly, this study validates HIFSM as the mediator that channels cyberchondria into action. While prior SSO applications in digital contexts often treated strain in generic terms such as "exhaustion" (Cao and Sun, 2018), the present study specifies a platform-linked form of fatigue that erodes both judgment and compliance. Showing that HIFSM conveys cyberchondria's effects to self-medication and therapy adherence sharpens understanding of how emotional exhaustion translates into concrete health decisions. This refinement encourages scholars to examine other domain-specific strains, for instance, vaccine information fatigue or mental-health content fatigue, as sequential mechanisms in digital health models.

Thirdly, this study reveals that trust in physicians weakens the negative impact of both cyberchondria and HIFSM on therapy compliance, yet does not mitigate the tendency to self-medicate. Such asymmetry suggests that trust functions more as a safeguard for ongoing treatment than as a deterrent to autonomous drug use, possibly because self-medication decisions often occur before any interaction with clinicians (Machado-Alba et al., 2014; Peng *et al*., 2020). This finding, in turn, refines previous work that treated trust solely as a direct antecedent of compliance (Erdem and Harrison-Walker, 2006; Lee and Lin, 2009) by revealing its contingent role, where strong relationships with physicians help patients stay on course once a regimen is prescribed but do not automatically curb first-step self-treatment. Scholars can thus use this distinction to probe cultural or contextual moderators, such as regulatory access to over-the-counter medicine, that may amplify or mute trust's protective capacity.

6.3 Practical implications

The findings offer valuable insights for both information system developers and healthcare providers in mitigating misinformation and promoting responsible online health-seeking behaviors. Since information overload fuels cyberchondria, developers should design interfaces that prioritize credible health content and embed source verification. Collaboration with healthcare professionals to curate guideline-based content can enhance trust and curb cyberchondria (Khan and Pandey, 2022). Meanwhile, healthcare providers can lead

health education campaigns that clarify the severity and likelihood of various health conditions (Laato *et al*., 2020b). Through offering clear, balanced information about health risks and outcomes, these campaigns can empower individuals to make informed decisions, alleviate unnecessary anxiety, and reduce unfounded health concerns.

Next, recognizing the significant impact of HIFSM in intensifying the adverse consequences of cyberchondria on health-related decisions underscores the imperative for mental health support, counseling, and stress management interventions (Dhir *et al*., 2018; Pang, 2024). To mitigate the effects of cyberchondria and HIFSM, healthcare providers should adopt digital interventions. Mobile apps that filter content, highlight credible sources, and deliver personalized health alerts can guide users toward trustworthy information while reducing information overload (Bakker *et al*., 2016; Lim, 2023). In addition, incorporating cognitive-behavioral therapy techniques into online platforms could help users manage anxiety triggered by excessive health-related content, teaching them healthier ways to process medical information (McMullan *et al*., 2019). These efforts are crucial for mitigating HIFSM's mediating role in health-related decision-making and promoting informed health behaviors.

Lastly, trust in healthcare providers plays a pivotal role in shaping health decisions. A strong physician-patient relationship enhances therapy compliance by buffering the negative effects of cyberchondria, yet it does not curb the tendency toward self-medication, suggesting that responsible self-medication can coexist with physician trust, particularly for minor conditions. This underscores the need for healthcare providers to guide patients on safe boundaries for self-care while ensuring transparency about reliable health information sources, both in clinical settings and on social media platforms (Wu *et al*., 2022; Peng *et al*., 2020). For information system developers, credibility should be enhanced by disclosing content sources and directing users to reputable health pages (Jaks *et al*., 2019). These efforts, in turn, should foster informed decision-making while balancing professional guidance with responsible patient autonomy

6.4 Concluding remarks and future directions

To this end, this study offered new insights into how threat perceptions (perceived susceptibility, perceived severity) and cognitive factors (online information trust, information overload) drive cyberchondria and HIFSM, shaping self-medication and therapy compliance. Integrating PMT, CLT, and the SSO model uncovered pathways where symptom perceptions and unverified online content fuel irrational medication behaviors. Findings highlighted HIFSM's mediating role in linking cyberchondria to self-medication and showed that physician trust can buffer the negative effects of both cyberchondria and HIFSM on therapy compliance.

Notwithstanding the contributions of this study, addressing its limitations is, inarguably, essential for guiding future research directions. The focus on the UK, for instance, offered valuable insights yet, concurrently, limited generalizability. Thus, future studies could include diverse populations to improve cross-cultural generalizability.

Furthermore, this study has not exhaustively explored all factors influencing cyberchondria. Personality traits, such as conscientiousness versus the need for cognitive closure, warrant further investigation. Buchanan (2020) and Riaz *et al* (2023) indicated that conscientious individuals may engage in a more critical evaluation of social media information, potentially mitigating anxiety caused by misinformation. Conversely, those with a high need for cognitive closure, as discussed by Quach and Lee (2023), may be more prone to anxiety due to their preference for quick answers and aversion to ambiguity.

Moreover, the study's findings on the limited role of trust in physicians in counteracting the effects of cyberchondria and HIFSM on self-medication prompt the need to explore cultural and contextual factors. Cultures emphasizing self-reliance in healthcare, as noted by Machado-Alba et al. (2014), may influence these dynamics, and the emerging role of AI-generated health information, such as chatbot diagnoses and health recommendations, presents a new frontier for research on its impact on health anxiety and decision-

making (Vismara *et al*., 2022).

Finally, subsequent phases of the study may benefit from integrating exhaustive longitudinal studies (i.e., panel data of an evolution model) to explore carry-over effects and experimental designs to elucidate the causal direction of the observed relationship. Incorporating measures that assess baseline levels of self-diagnosis tendencies before exposure to online health information could also assist in establishing temporal precedence.

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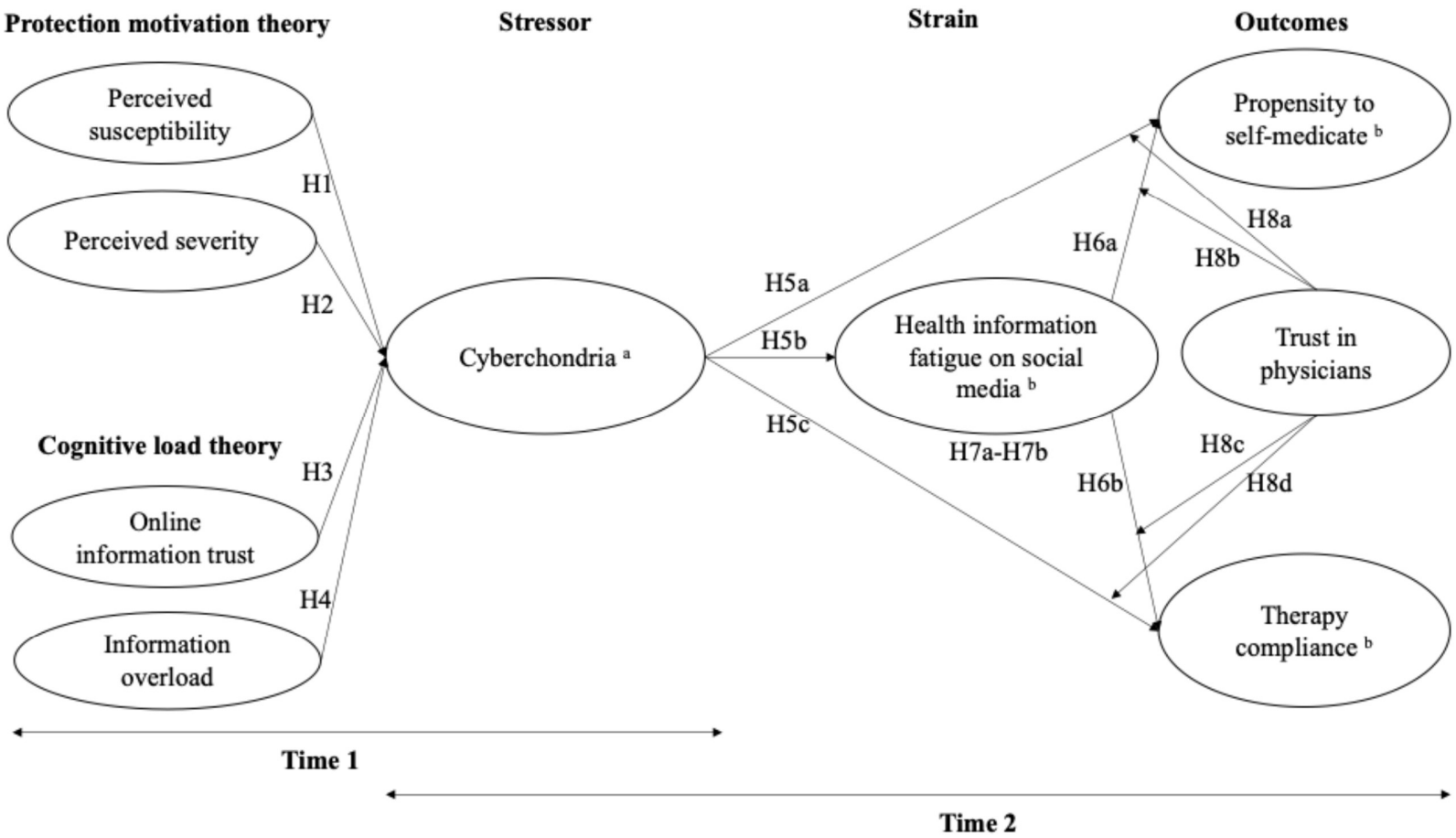
Figure 1. Research model



Notes: [a] means that cyberchondria and health information fatigue on social media were controlled using gender, age, education level, frequency of health information search, social media-health literacy, and social desirability (marker). [b] means that propensity to self-medicate and therapy compliance were controlled using gender, age, education level, and social desirability (marker).

Source: Authors' own illustration.

Figure 2. Data collection

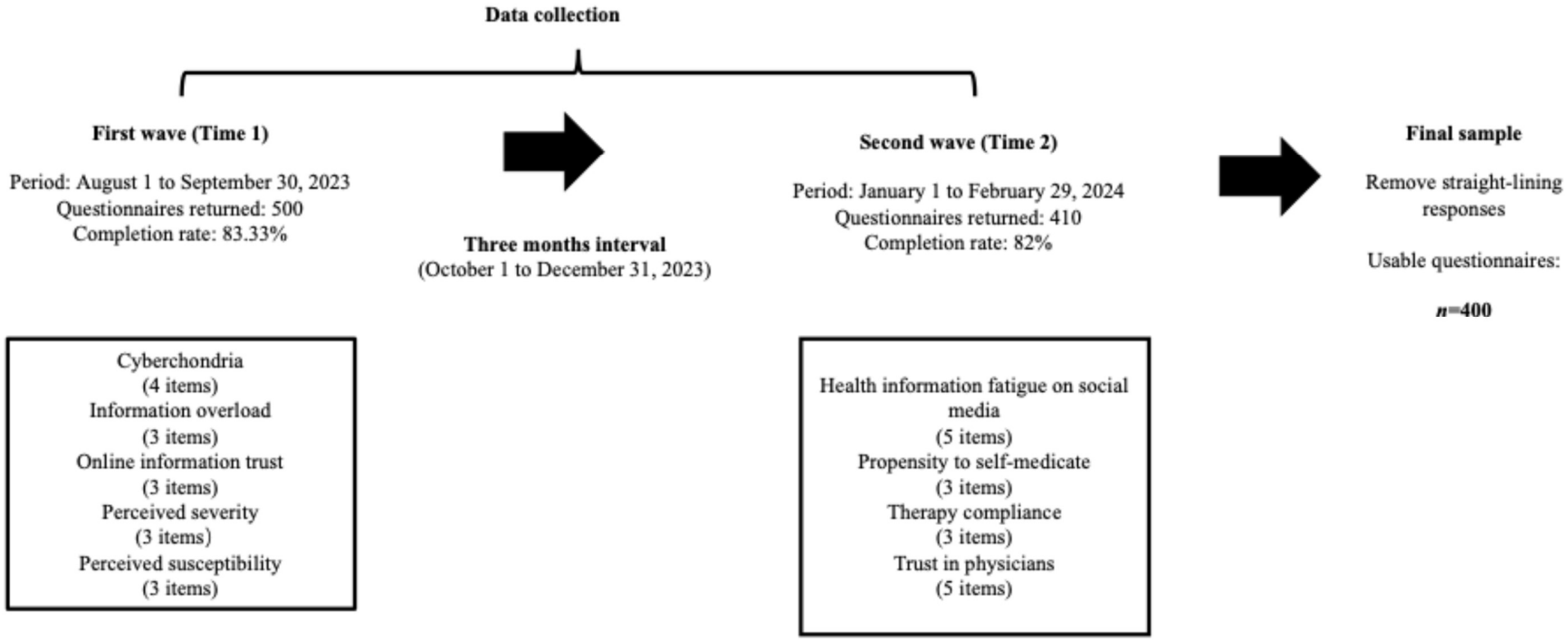
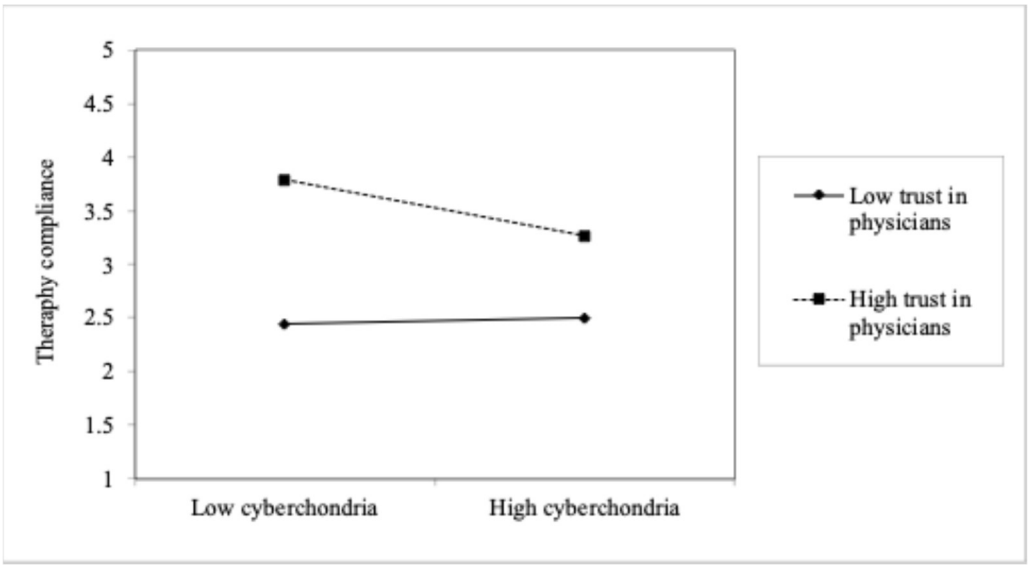
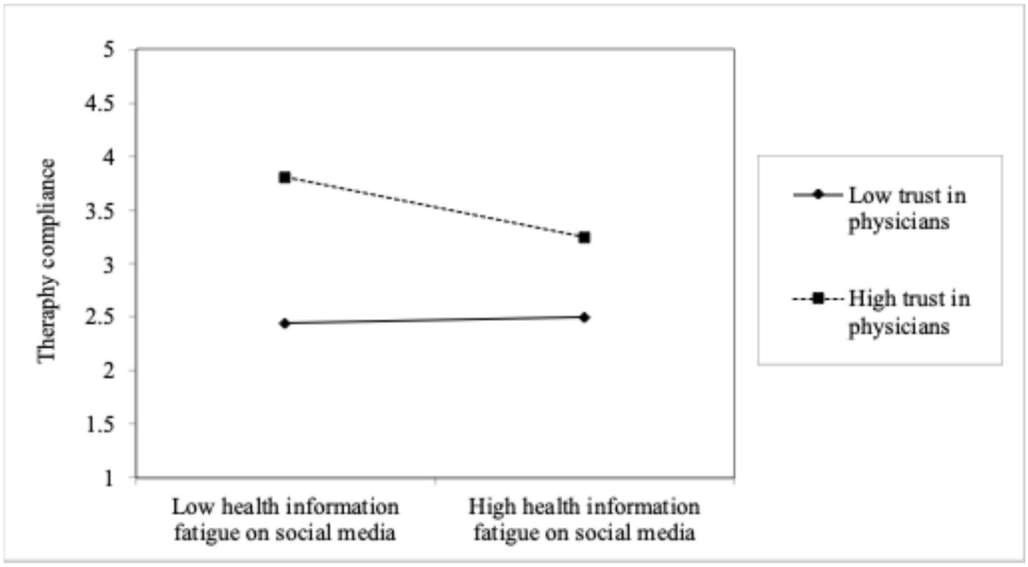


Figure 3. Moderation relationships

Panel	Interaction Plot
A	
B	

Notes: Panel A is the interaction plot of cyberchondria × trust in physicians on therapy compliance. Panel B is the interaction plot of health information fatigue on social media × trust in physicians on therapy compliance.

Source: Authors' own illustration.

Table 1. Profile of participants

	Characteristic	Frequency (n = 400)	Percentage (%)
Gender	Female	258	64.5
	Male	142	35.5
Age	27 to 34 years old (born in 1989 to 1996)	255	63.8
	35 to 42 years old (born in 1981 to 1988)	145	36.3
Education level	Undergraduate degree (B.A., B.Sc., etc.)	263	65.8
	Graduate degree (M.A., MBA, M.Sc., etc.)	125	31.3
	Postgraduate degree (DBA, Ph.D., etc.)	12	3.0
Living situation	Alone	132	33.0
	Shared apartment / house	200	50.0
	Family / children	68	17.0
Have you searched for health information via social media, at least two to three times in the past two months?	Yes	400	100.0
	No	0	0.0
Do you have any severe medical records?	Yes	0	0.0
	No	400	100.0
Duration of access to social media	1–3 hours	153	38.3
	4–6 hours	162	40.5
	More than 6 hours	85	21.3
Types of social media use to search online health information (*n*=1,126) *	Facebook	138	12.3
	Instagram	214	18.9
	LinkedIn	151	13.4
	Snapchat	258	22.9
	Twitter (X)	365	32.4
Frequency of health information searched on social media	Seldom	63	15.8
	Occasionally	170	42.5
	Frequently	143	35.8
	Always	24	6.0
Types of online health information searched (*n*=2,654) *	Access to healthcare	297	11.2
	Chronic disease	75	2.8
	COVID-19	214	8.1
	Depression	302	11.4

Hand, foot, and mouth disease (HFMD)	110	4.1
HIV/AIDS	78	2.9
Influenza	287	10.8
Injury and violence	93	3.5
Mental health	361	13.6
MonkeyPox	50	1.9
Obesity or overweight	219	8.3
Physical activity and nutrition	242	9.1
Tobacco	54	2.0
Vaccines and immunization	272	10.2

Notes: * means the respondent can answer multiple options.

Source: Authors' own compilation.

Table 2. Assessment of convergent validity and internal consistency

Construct	**Item**	**Convergent validity**		**Internal consistency**
		Factor loading	**Average variance extracted**	**Composite reliability**
Cyberchondria (T1)	CYB1	0.881	0.759	0.926
	CYB2	0.851		
	CYB3	0.896		
	CYB4	0.856		
Information overload (T1)	IO1	0.919	0.837	0.939
	IO2	0.927		
	IO3	0.899		
Online information trust (T1)	OIT1	0.928	0.843	0.941
	OIT2	0.927		
	OIT3	0.900		
Perceived severity (T1)	PSEV1	0.873	0.767	0.908
	PSEV2	0.893		
	PSEV3	0.860		
Perceived susceptibility (T1)	PSUS1	0.910	0.840	0.940
	PSUS2	0.929		
	PSUS3	0.910		
Health information fatigue on social media (T2)	HIFSM1	0.879	0.728	0.930
	HIFSM2	0.900		
	HIFSM3	0.718		
	HIFSM4	0.900		
	HIFSM5	0.856		
Propensity to self-medicate (T2)	PSM1	0.904	0.834	0.938
	PSM2	0.922		
	PSM3	0.914		
Social desirability (MV)	SD1	0.833	0.773	0.960
	SD2	0.765		
	SD3	0.863		
	SD4	0.917		
	SD5	0.924		

	SD6	0.927		
	SD7	0.914		
Social media-health literacy (CV)	SMHL1	0.825	0.681	0.945
	SMHL2	0.837		
	SMHL3	0.830		
	SMHL4	0.836		
	SMHL5	0.820		
	SMHL6	0.810		
	SMHL7	0.815		
	SMHL8	0.829		
Therapy compliance (T2)	TC1	0.907	0.846	0.943
	TC2	0.925		
	TC3	0.927		
Trust in physicians (T2)	TP1	0.732	0.737	0.933
	TP2	0.869		
	TP3	0.884		
	TP4	0.897		
	TP5	0.900		

Notes: T1 means the data was collected in Wave 1. T2 means the data was collected in Wave 2. CV means control variable. MV means marker variable. Item statement and source can be found in Appendix D.

Source: Authors' own compilation.

Table 3. Assessment of discriminant validity

Construct	1	2	3	4	5	6	7	8	9	10	11
1. Cyberchondria (T1)	***0.871***	0.675	0.720	0.580	0.566	0.427	0.539	*0.196*	0.572	0.177	0.369
2. Health information fatigue on social media (T2)	0.743	***0.853***	0.762	0.583	0.504	0.468	0.562	*0.289*	0.492	0.210	0.297
3. Information overload (T1)	0.779	0.696	***0.915***	0.585	0.520	0.442	0.529	*0.201*	0.539	0.245	0.356
4. Online information trust (T1)	0.645	0.536	0.647	***0.918***	0.420	0.462	0.442	*0.287*	0.517	0.218	0.333
5. Propensity to self-medicate (T2)	0.627	0.457	0.577	0.465	***0.913***	0.266	0.419	*0.229*	0.468	0.114	0.284
6. Perceived severity (T1)	0.486	0.418	0.498	0.524	0.298	***0.876***	0.600	*0.281*	0.436	0.326	0.382
7. Perceived susceptibility (T1)	0.595	0.512	0.583	0.485	0.462	0.528	***0.916***	*0.248*	0.402	0.176	0.291
8. Social desirability (MV)	0.223	*0.255*	0.249	*0.244*	*0.205*	*0.243*	*0.210*	***0.879***	*0.263*	*0.062*	*0.250*
9. Social media-health literacy (CV)	0.625	0.531	0.586	0.561	0.509	0.484	0.434	0.296	***0.825***	0.309	0.518
10. Therapy compliance (T2)	0.198	0.233	0.269	0.239	0.126	0.364	0.194	0.090	0.285	***0.920***	0.573
11. Trust in physicians (T2)	0.435	0.345	0.416	0.386	0.340	0.443	0.343	0.275	0.457	0.636	***0.858***

Notes: Diagonal values in bold italics represent the square root of the average variance extracted. The heterotrait-monotrait (HTMT) ratio of correlations (< 0.85) appears below the diagonal while inter-construct correlations are shown above the diagonal. Values in regular italics indicate inter-construct correlations below 0.3 for the theoretically unrelated marker variable (i.e., social desirability) with other variables of interest.

Source: Authors' own compilation.

Table 4. Assessment of the structural model

Wave	Test	Relationship	Standard beta (Standard error)	*t*-value	*p*-value
1	Direct effect	H1: Perceived susceptibility → Cyberchondria	0.175 (0.046)	3.804	0.000
		H2: Perceived severity → Cyberchondria	0.121 (0.047)	2.574	0.000
		H3: Online information trust → Cyberchondria	0.199 (0.049)	4.061	0.000
		H4: Information overload → Cyberchondria	0.502 (0.049)	10.245	0.000
	Control variable	Age → Cyberchondria	0.028 (0.034)	0.824	0.098
		Education level → Cyberchondria	0.070 (0.056)	1.061	0.188
		Frequency of health information search → Cyberchondria	0.024 (0.083)	0.289	0.160
		Gender → Cyberchondria	0.093 (0.146)	0.637	0.408
		Social media-health literacy → Cyberchondria	0.120 (0.070)	1.714	0.041
		Social desirability → Cyberchondria	0.062 (0.053)	1.170	0.096
2	Direct effect	H5a: Cyberchondria → Propensity to self-medicate	0.447 (0.060)	7.950	0.000
		H5b: Cyberchondria → Health information fatigue on social media	0.675 (0.035)	19.286	0.000
		H5c: Cyberchondria → Therapy compliance	-0.120 (0.070)	-1.714	0.045
		H6a: Health information fatigue on social media→ Propensity to self-medicate	0.132 (0.061)	2.164	0.015
		H6b: Health information fatigue on social media→ Therapy compliance	-0.125 (0.070)	-1.786	0.044
	Mediating effect	H7a: Cyberchondria → Health information fatigue on social media→ Propensity to self-medicate	0.089 (0.041)	2.171	0.036
		H7b: Cyberchondria → Health information fatigue on social media→ Therapy compliance	-0.084 (0.042)	-2.000	0.041
	Moderating effect	H8a: Cyberchondria × Trust in physicians → Propensity to self-medicate	-0.010 (0.033)	-0.303	0.381
		H8b: Health information fatigue on social media × Trust in physicians → Propensity to self-medicate	0.016 (0.035)	0.457	0.321
		H8c: Health information fatigue on social media × Trust in physicians → Therapy compliance	-0.151 (0.051)	-2.961	0.002
		H8d: Cyberchondria × Trust in physicians → Therapy compliance	-0.145 (0.055)	-2.636	0.004
	Control variable	Age → Health information fatigue on social media	0.011 (0.039)	0.282	0.385
		Education level → Health information fatigue on social media	-0.005 (0.038)	-0.132	0.450
		Social desirability → Health information fatigue on social media	0.101 (0.070)	1.443	0.071
		Gender → Health information fatigue on social media	-0.004 (0.032)	-0.125	0.463
		Age → Propensity to self-medicate	0.097 (0.086)	1.128	0.127
		Education level → Propensity to self-medicate	0.077 (0.076)	1.013	0.172
		Social desirability → Propensity to self-medicate	0.102 (0.075)	1.360	0.096
		Gender → Propensity to self-medicate	0.093 (0.064)	1.453	0.082
		Age → Therapy compliance	0.104 (0.073)	1.425	0.087
		Education level → Therapy compliance	-0.114 (0.075)	-1.520	0.054
		Social desirability → Therapy compliance	0.117 (0.078)	1.500	0.057
		Gender → Therapy compliance	0.012 (0.067)	0.179	0.374
Quality criteria		**Key target endogenous construct (Time)**	**R^2**	**Q^2 predict**	**Durbin-Watson**
		Cyberchondria (Wave 1)	0.603	0.587	NA
		Health information fatigue on social media (Wave 2)	0.456	0.484	1.954
		Propensity to self-medicate (Wave 2)	0.336	0.312	1.952
		Therapy compliance (Wave 2)	0.337	0.310	1.953

Notes: NA means not applicable in Wave 1.

Source: Authors' own compilation.