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Overcoming Health Fears: How do online peers help patients with chronic pain?

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ABSTRACT

This study investigates how online interactions influence anxiety levels in patients with chronic musculoskeletal pain by examining the impact of social interactions within online health communities. We used actor-oriented modelling to analyse the online interactions of 200 users with musculoskeletal pain in an English-speaking online health community over three years. This method focuses on how people make decisions and interact within a network. We examined the behaviours and network dynamics of influential users with different anxiety levels to see how they engage socially online and if they adopt (non-)anxious attitudes from their peers. The findings suggest that although online social interactions could benefit anxious patients, more anxious individuals tend to experience more social isolation online. Moreover, individuals tend to adopt anxious attitudes from online peers, highlighting the influence of social interactions on emotional well-being. Contrary to homophily assumptions, we observed an "opposites anxiety attract" phenomenon—users frequently formed ties with others whose anxiety levels differed from their own. This dynamic indicates both encouraging and concerning aspects of virtual peer influence. While online health communities can reduce anxiety in patients with musculoskeletal pain, the effectiveness of social support depends on individuals' anxiety levels and their online interactions. Understanding these nuances is important for optimising digital platforms to support those struggling with anxiety and depression related to chronic pain.

1. Introduction

Chronic pain significantly affects patients' quality of life, often resulting in psychological challenges such as anxiety, depression, and social isolation. Previous studies have extensively documented that chronic pain and depression are common and mutually interactive comorbidities, with anxiety and depression playing a role in increasing the likelihood of developing chronic pain and vice versa (Williams et al., 2006). This population is particularly vulnerable to anxiety and depression, as the condition often limits physical functioning and disrupts social life (Mullins et al., 2023; Todd et al., 2022; Lerman et al., 2015). With approximately one in five adults in Europe and the United States experiencing chronic pain, it is increasingly recognised as a serious public health and economic problem worldwide (Stubhaug et al., 2024), in part due to decreased productivity and the potential for addiction associated with widespread use of pain medications (Kuehn, 2018). Existing research recognises the central role that social support plays in providing patients with comfort and information, thereby improving their knowledge, coping mechanisms, and overall well-being (Cacioppo et al., 2009; Verdonck-de Leeuw et al., 2007). Due to the chronicity of their symptoms, patients with a chronic pain condition have more frequent contact and longitudinal relationships with primary care providers (Matthias et al., 2010). However, it has been observed that patients do not always consider the social support provided by their healthcare providers sufficient (Becker, 2020). As a consequence, patients often seek emotional support from their personal network, such as friends and family. However, their emotional involvement and sometimes lack of understanding, as they probably have not experienced a similar situation previously, can complicate their ability to support the patient (Ell, 1996). Given these challenges, many patients turn to online health communities (OHCs) for emotional support, practical advice, and validation (Zambelli et al., 2021; Tang et al., 2018; Wang et al., 2017; Zhao and Zhang, 2017). The accessibility, anonymity, and shared experiences in online health communities (OHCs) make them a particularly valuable source of support for chronic pain patients, allowing them to express their anxieties and seek advice in a nonjudgmental environment (Kostova et al., 2015; Santer et al., 2015). By facilitating peer-to-peer engagement, these platforms allow individuals to connect

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with others facing similar difficulties, potentially reducing feelings of isolation and mitigating negative psychosocial effects such as anxiety. This aligns with Kenny's social interaction model, which highlights how reciprocity and mutual influence within dyadic relationships shape emotional and behavioural outcomes over time (Kenny, 2019).

Chronic pain patients often seek support in online communities due to the long-term nature of their condition and its emotional impact. Research highlights that individuals with chronic pain experience heightened levels of anxiety and depression, often driven by the unpredictability and persistence of their symptoms (Kostova et al., 2015; Santer et al., 2015). Anxiety levels are not static and may evolve over time, possibly influenced by the support and advice exchanged with peers online (Baumgartner et al., 2023). As such, the psychological challenges of chronic pain patients make them an ideal population for examining the co-evolution of emotional states and social network dynamics, particularly in online health communities where anonymity and accessibility reduce barriers to participation (Premanandan et al., 2024).

Previous studies have shown that online social interactions can reduce anxiety by providing patients with access to peer support and diverse perspectives. For example, Tan and Goonawardene (2017) found that patients who actively seek health information online report improved communication with physicians, while Zhao and Zhang (2017) emphasise the role of peer interactions in fulfilling emotional and informational needs. Similarly, Kostova et al. (2015) demonstrated the value of virtual support systems for mitigating feelings of isolation among individuals with chronic illnesses. However, the mechanisms by which anxiety evolves in these communities remain underexplored. Understanding these dynamics involves examining how network structures influence and are influenced by human behaviour, focusing on what drives the spread of attitudes and behaviours in communities. (Renzini et al., 2024). Building on social network theory, we explore the mechanisms by which attitudes, behaviours, and emotions spread and take root. We emphasise the role of reciprocity, homophily, and emotional contagion in these processes (Centola and van de Rijt, 2015; Wasserman and Faust, 1994). By using network theory, this study contributes to understanding how anxiety both *shapes* and *is shaped* by social ties in OHCs.

1.1. Hypotheses

We explore both stable relationships and dynamic exchanges to show how networks and individual actions influence each other. To do so, we specifically look at reciprocity and homophily in OHCs (Centola and van de Rijt, 2015; Wasserman and Faust, 1994). Reciprocity refers to mutual exchanges between members like giving and receiving advice (Gouldner, 1960), while homophily refers to connecting with similar others, such as those with similar anxiety levels (Centola, 2011). Our study thereby builds on core social network theory (Wasserman and Faust, 1994; Granovetter, 1973) and recent findings on emotional co-regulation in online networks (Fang and Mushtaque, 2024; Centola and van de Rijt, 2015; Sillence, 2010).

With anxiety as both a precursor to chronic pain and a driver of social interactions (McMullan et al., 2019; Muse et al., 2012), we explore how anxiety can shift in response to social support and how these shifts further shape subsequent interactions. Recent work underscores the dual role of online health communities (OHCs) in mitigating anxiety and fostering social support (Stuart et al., 2021; McMullan et al., 2019; Wang et al., 2021; Fang and Mushtaque, 2024). For example, Zambelli et al. (2021) show that shared experiences in OHCs reduce isolation, while Deng et al. (2023) indicate that anxiety levels can either be mitigated or exacerbated by the intensity of online interactions. Similarly, the thematic analysis by Smith-Merry et al. (2019) highlights the importance of peer connections in mental health forums, where emotional support often determines user engagement. Nevertheless, limited research has examined how anxiety levels evolve alongside social support networks among chronic pain patients. Our study aims to address this gap by offering insights that healthcare professionals can use to understand patient interactions online and their potential outcomes.

1.2. Social interactions

Our research integrates social contagion theory (Marsden and Friedkin, 1993) with insights from health behaviour theories (Willis, 2018) and network dynamics theory (Steglich et al., 2010). This multidisciplinary approach extends the understanding of co-evolutionary mechanisms between emotional states (specifically anxiety) and social ties in digital health contexts. Additionally, we draw on Kenny's social interaction model, which emphasises actor and partner effects: how one individual's emotional state (actor effect) influences others' perceptions and reactions (partner effect), and vice versa (Kenny, 2019). We hypothesise that, over time, patients' anxiety levels influence their willingness to engage with or avoid social support. Our framework analyses coevolution in two ways: (1) how interactions among patients emerge or change over time, and (2) how similarities in anxiety levels may converge (or diverge) within the community. Refer to Table 1 for an overview of our framework and hypotheses.

1.2.1. Patient's anxiety affects outgoing network ties

Negative emotional states, such as depression and anxiety, are known to inhibit social interaction, resulting in fewer and weaker social ties that can further reinforce negative attitudes (Steger and Kashdan, 2009; Elmer and Stadtfeld, 2020). Although it appears that anxious individuals who can seek social support from peers online may be more likely to overcome their negative emotions (Cacioppo et al., 2009), giving advice requires not only knowledge and experience but also confidence, self-efficacy, and emotional resilience (Bandura and Wessels, 1997; Ryan and Deci, 2000). These attributes tend to be diminished in anxious individuals, making them less likely to engage in outward behaviours such as offering advice—even if they actively seek support themselves. Thus,

Hypothesis 1. The more anxious a person appears to be, the less advice the person will send to peers.

1.2.2. Patient's anxiety affects incoming network ties

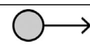
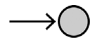
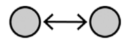
Previous studies indicate that online peer support networks are important sources of empathy and sympathy (Brownlie and Shaw, 2019), suggesting that visible fear or anxiety in one user (actor effect) may trigger supportive responses from others (partner effect). Kenny's model underscores how the expression of emotion by one individual can shape the behavioural and emotional responses of those around them (Kenny, 2019). In offline contexts, people tend to feel compelled to assist those who appear vulnerable (Hargreaves et al., 2018), and evidence suggests this principle of empathy-driven help applies to digital settings as well (Naslund et al., 2014). Anxious signals (e.g., posts suggesting desperation or fear) may motivate peers to provide more advice, hoping to alleviate the person's distress. We thus hypothesise the following:

Hypothesis 2. The more anxious a person appears to be, the more advice peers will send to the person.

1.2.3. Incoming network ties affect patient's anxiety

Social support has long been recognised as a protective factor against anxiety (Cacioppo et al., 2009; Elmer and Stadtfeld, 2020). In online health communities, people can post questions to which their peers can respond. In the form of answers to these questions, emotional and informational support are the types of social support that are the most widely exchanged (Smailhodzic et al., 2016). From a network perspective, incoming ties can create a sense of social integration, acting as a buffer against social isolation that tends to exacerbate

Table 1
Conceptual framework: Overview of hypotheses.

			Anxiety influences network ties	Network ties influence anxiety
Interaction	Sender [ego]		The more anxious a person appears to be, the less advice the person will send to others (*action* $-H_1^-$)	
	Receiver [alter]		The more anxious a person appears to be, the more advice peers will send to the person (*attraction* $-H_2^+$)	The more ties a person receives, the less anxious he/she will subsequently be (*reaction* $-H_3^-$)
Similarity	Sender-receiver [dyad]		A person will have more ties with peers whose anxiety levels are similar to their own (*homophily* $-H_4^+$)	Over time, a person will adopt the (non-)anxious attitude of others he/she is connected to (*assimiliation* $-H_5^+$)

anxiety (Smith and Christakis, 2008). Receiving advice further signals that peers believe in an individual's ability to manage challenges they are facing, potentially increasing perceived self-efficacy and reducing subsequent anxiety (Bandura and Wessels, 1997; Uchino, 2006). Thus, we expect:

Hypothesis 3. The more advice ties a person receives, the less anxious they will be subsequently.

1.3. Similarity and assimilation over time

1.3.1. Similarity

Homophily, or the tendency of individuals to associate with others who are similar to themselves – in terms of interests, beliefs, and behaviours – plays an important role in both the formation and maintenance of social networks and subsequent behaviour changes (McPherson et al., 2001; Centola, 2011). In line with previous findings on homophily (Aral et al., 2009; Aiello et al., 2012; Bisgin et al., 2012), we suggest that anxious individuals are more likely to seek out peers who are also anxious, and vice versa. Although homophily can lead to increased feelings of safety and comfort (Ertug et al., 2022), it could also lead to an echo chamber effect, where individuals only ever encounter views and opinions that align with their own (Cinelli et al., 2021; Wollebæk et al., 2019). This could be particularly troubling in the case of negative emotions, such as anxiety, where it could lead to fear-laden echo chambers where individuals inadvertently reinforce their own anxiety. We hypothesise the following:

Hypothesis 4. A person will have more ties with peers whose anxiety levels are similar to their own.

1.3.2. Assimilation

Assimilation refers to the process by which individuals come to share the behaviours or beliefs typical of their social group (Morrison, 2002). In the context of emotional contagion, Kenny's emphasis on reciprocal influence suggests that the anxiety level of one user can be "transferred" through repeated interactions to another (Kenny, 2019). As outlined by social contagion research (Coiera, 2013; Hatfield et al., 2011), this occurs when an actor is consistently exposed to the emotional expressions of connected peers (partner effects). In line with the theory of social learning of fear (Olsson and Phelps, 2007), anxious peers can amplify an individual's own anxiety, while less anxious peers can help reduce it over time. Thus, anxiety levels are not static; they evolve in parallel with the social environment over time:

Hypothesis 5. Over time, a person will adopt the anxiety levels of others with whom they are connected.

2. Materials and methods

Several studies, including Rueger et al. (2023), De Laat (2023), have documented the systematic steps required to collect, extract, and clean data from online communities. Guided by these protocols, the dataset in this study was constructed by gathering discussion threads and user interactions over a defined observation period, and then cleaning the dataset. This dataset was then analysed using 'Simulation Investigation for Empirical Network Analysis' (SIENA) software, developed by Snijders (2005).

2.1. Analyses

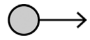
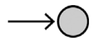
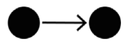
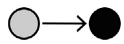
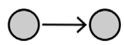
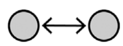
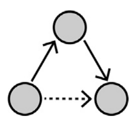
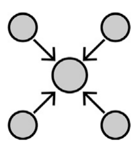
We explore the bidirectional relationship between network structures and individual behaviour, focusing on how social connections form, persist, or dissolve, as well as how these changes affect – and are affected by – users' anxiety levels. Simulation Investigation for Empirical Network Analysis (SIENA) (Snijders, 2005) was employed to study the longitudinal interplay between anxiety (as an actor attribute) and evolving social networks. SIENA is designed to model both changes in network structure and changes in actor attributes over multiple time points (Ripley et al., 2011; Snijders et al., 2010). Changes in anxiety levels and social connections are assumed to occur continuously between observed time slices, and the most likely sequences of unobserved transitions are simulated based on the actual data. This actor-based modelling framework assumes that individuals can, at random moments, initiate or dissolve social connections and modify their expressed anxiety level. The approach enables an examination of small "micro steps", showing how network structure and anxiety co-evolve. Lastly, we used a SIENA feature called 'joiners and leavers' to account for periods of inactivity, recognising that not all users contribute consistently throughout each observed interval.

Following Snijders et al. (2010), we included the network control variables reciprocity ("if you support me, then I will also support you") and transitivity ("friends of my friends are my friends") in all models by default. Throughout this process, we evaluated the goodness of fit of the models and added network control variables until a sufficient fit was achieved. In addition to the default parameters mentioned above, we included four effects for each control variable: sender, receiver, and similarity effects on network ties, as well as the effect of each control variable on anxiety levels (see Table 2). As we controlled for personality, the final models only considered the personality effects that were significant in the separate control models. Following other studies (e.g. Burk et al., 2007; Ripley et al., 2011), we did so to prevent inflated standard errors and convergence issues that could arise from including too many non-significant parameters.

2.2. Sample

We gathered interaction data from a prominent English-speaking online health community, selecting a subgroup focused on patients

Table 2
Summary of actor-specific and network effects included in empirical model specifications.

Variable	Visualisation	Included to account for	Network statistics
Actor			
Sender		Tendency of individuals with certain behaviour (e.g., high anxiety) to initiate connections with others	$v_i\, x_{i+}$
Receiver		Tendency of individuals with certain behaviour (e.g., high anxiety) to attract connections from others	$\sum_j x_{ij}\, v_j$
Homophily		Likelihood of connections forming between people who share similar characteristics (e.g., anxiety levels)	$\sum_j x_{ij}\,(sim^v_{ij} - \widehat{sim^v})$
Assimilation		Tendency of individuals to adopt similar behaviours (e.g., anxiety levels) as those they interact with	$x_{i+}^{-1} \sum_j x_{ij}\,(sim^z_{ij} - \widehat{sim^z})$
Network			
Density		Overall likelihood of connections forming within the network (i.e., how "connected" the network is)	$\sum_j x_{ij}$
Reciprocity		Tendency for relationships to be mutual (e.g., if A supports B, then B also supports A)	$\sum_j x_{ij}\, x_{ij}$
Transitivity		Tendency for a person's connections to also be connected to each other (e.g., A knows B, and B knows C, so A knows C)	$\sum_{j,h} x_{ij}\, x_{ih}\, x_{hj}$
Popularity spread		Likelihood that individuals with more connections (i.e., "popular" people) will influence others' behaviours	$z_i \sum_j x_{ij}$

Note. $x_{ij} = 1$ indicates presence of a tie from i to j while $x_{ij} = 0$ indicates absence. The dependent behaviour variables are denoted v_i.

with chronic musculoskeletal pain as our initial sample. Subsequently, we selected a 3-year time span, starting once the community had established a substantial and growing user base. Following recommendations for stochastic actor-based modelling (Snijders et al., 2010), it was deemed appropriate to work with a network of a few hundred nodes to minimise missing interactions from inactive users and to keep the computational complexity at a manageable level. To do so, we narrowed the sample down to the 200 most influential superusers based on the volume of advice they contributed within that period using the *keyplayer* algorithm in R (An and Liu, 2016). We define 'superusers' as those who contribute disproportionately to overall community activity. For instance, our 200 superusers, representing approximately 2.9% of the total of 6,794 users, contributed 56.2% of all advice exchanges. This aligns with previous research (van Mierlo et al., 2012; De Simoni et al., 2020), which shows that a very small subset of highly active users often account for most interactions, making them the most important for a stable, active and well-connected network. In fact, superusers have been found to produce the majority of visible content, with the rest of users mostly reading or contributing occasionally (Van Mierlo et al., 2014). Moreover, stochastic actor-oriented models such as SIENA are optimised for moderately sized networks to balance computational feasibility and model accuracy (Steglich et al., 2010). When filtering the contributions to only include those that were in response to another user who is also part of the 200-user subset, we counted a total of 6,866 ties across all six timespans. Table A.1 in the Appendix compares the 200 superusers to the full community on several important activity metrics. Superusers tend to be members of the community for longer (days since registration: $M = 902.94, SD = 396.59$ vs. $M = 748.90, SD = 505.51$), send on average nearly twice as many replies to peers ($M = 17.63, SD = 113.05$ vs. $M = 9.01, SD = 49.95$), and initiate far more threads ($M = 17.71, SD = 18.45$ vs. $M = 2.27, SD = 25.07$). These differences further illustrate that this relatively small group of active users contributes substantially to the volume of activity and cohesion in the network.

While collecting the interaction data to include all interactions during the 3-year period, we also defined six points in time to evaluate. The six points in time were established at the beginning of the entire period (t_0), after six months (t_1) and every six months ($t_2 - t_4$) until the end of the three-year period (t_5). Demographic details such as age, gender, and location were not consistently reported by users, although an internal survey of the online health community operators indicated that 68% of the users were women, 82% were at least 35 years old, and most resided in the United States or the United Kingdom.

2.3. *Measures*

2.3.1. *Anxiety*

Anxiety was measured on a scale from 0 to 5 using the Linguistic Inquiry and Word Count (LIWC) sentiment dictionary, a validated tool for linguistic analysis (e.g., Tausczik and Pennebaker, 2010; Boyd et al., 2022; Donohue et al., 2014). LIWC has been widely adopted in psychological and linguistic research to quantify emotional states, including anxiety (Burkhardt et al., 2022; McDonnell et al., 2020; Boyd et al., 2022; Guntuku et al., 2019). For example, Donohue et al. (2014) validated LIWC dictionaries against manually coded emotional constructs, while Yarkoni (2010) demonstrated LIWC's robustness in detecting personality traits and emotional variability in online interactions. The 0–5 coding scheme was adapted from previous LIWC validation research (Donohue et al., 2014; Yarkoni, 2010; Burkhardt et al., 2022), aiming to capture a broad spectrum of anxiety from neutral (0) to highly distressed (5). Phrases indicating more severe worry or fear were scored at higher levels, consistent with prior findings linking anxiety-related language to cyberchondriasis and stress (Muse et al., 2012). A graded scale rather than a binary one allowed us to track

Table 3
Descriptive statistics and pair-wise correlations of study variables.

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Behaviour: Anxiety																				
1. Time 1	0.81	1.42	0.00	5.00																
2. Time 2	1.46	1.59	0.00	5.00	−0.4*															
3. Time 3	1.33	1.49	0.00	5.00	−0.45	0.33*														
4. Time 4	1.24	1.54	0.00	5.00	−0.23	0.52*	0.73*													
5. Time 5	1.08	1.43	0.00	5.00	0.03	0.16	0.06*	−0.17*												
6. Time 6	0.73	1.26	0.00	5.00	−0.63	0.35	0.11	0.13*	0.03*											
Network: No. of advice ties sent/person																				
7. Time 1	14.10	16.25	1.00	88.00	0.01	0.14*	0.03	0.12	0.04	0.22										
8. Time 2	18.89	23.60	1.00	161.00	0.14	0.32	0.02*	0.15	0.11	0.09*	0.87*									
9. Time 3	14.63	19.98	1.00	125.00	0.00	0.3	0.02	0.13*	−0.1*	0.05*	0.85*	0.9*								
10. Time 4	9.20	12.83	1.00	79.00	−0.02	0.32	0.17	0.34	−0.06*	0.25*	0.87*	0.87*	0.89*							
11. Time 5	8.21	13.51	1.00	78.00	0.07	0.15	−0.07	0.07	0.02	0.15*	0.96*	0.82*	0.86*	0.88*						
12. Time 6	8.04	12.39	1.00	65.00	−0.02	0.26	0.1	0.28	−0.11	0.25	0.94*	0.87*	0.89*	0.94*	0.93*					
Control variables: Person characteristics																				
13. Openness	0.69	0.22	0.05	1.00	0.13	−0.08	−0.15*	0.00	0.18	−0.2*	0.41	0.34	0.29	0.31*	0.37*	0.23				
14. Conscientiousness	0.34	0.21	0.02	0.95	−0.26	−0.24	−0.29	−0.69	0.19*	0.00	−0.03	0.04*	0.05*	−0.15	−0.07	−0.16	0.24			
15. Extraversion	0.03	0.05	0.00	0.43	−0.23	0.04	−0.4	−0.53	0.19	0.00	−0.06	0.06	0.07	−0.22	−0.07	−0.17	0.3*	0.79*		
16. Agreeableness	0.40	0.25	0.01	1.00	−0.3	−0.08	0.17	−0.13	0.19*	0.38*	−0.46	−0.37	−0.51*	−0.47*	−0.55*	−0.4	−0.54*	0.26*	0.21*	
17. Neuroticism	0.22	0.14	0.01	0.77	−0.21	−0.17	−0.39	−0.6	0.06*	−0.11*	0.23	0.21	0.33*	0.12*	0.25*	0.1	0.45*	0.85*	0.66*	−0.23

* Correlations marked with an asterisk are significant at $p < .05$.

Note. $N = 200$. The data span a three-year period and were divided into six equal intervals. Time 1 includes all interactions from months 1–6, Time 2 includes months 7–12, Time 3 covers months 13–18, Time 4 covers months 19–24, Time 5 covers months 25–30, and Time 6 covers months 31–36.

fluctuations in anxiety over time (Watson et al., 1988a,b; Himmelstein et al., 2018).

2.3.2. Network ties

We constructed a so-called ‘who replies to whom’ network by examining each instance of advice or information exchanged within the sample. When a user posted a question and received a response, an ingoing tie was assigned to that user; the user who provided the response received an out-going tie. These advice-based ties form the network data used by SIENA to analyse network evolution and its co-evolution with anxiety.

2.3.3. Control variables

Previous studies have shown that in addition to commonly used demographic variables such as gender and age, which are not available to us in our study, personality traits can influence the creation of social network ties (Schulte et al., 2012). In addition, personality traits can also influence the degree to which a patient is likely to experience anxiety, depression, and fear (Gustin et al., 2016; Zeng et al., 2016; Klein et al., 2011).

To account for differences in personality, personality traits were derived using linguistic markers identified through the Big Five (OCEAN) framework, which assesses openness, conscientiousness, extraversion, agreeableness, and neuroticism. The Big Five framework was chosen for its well-established relevance in predicting social behaviour and emotional regulation, particularly in online contexts. For example, neuroticism has been linked to higher anxiety levels (Zeng et al., 2016), while extraversion is associated with increased social engagement (Gosling et al., 2003). These traits are important for understanding how personality influences advice-seeking and giving behaviours in online health communities. Previous studies such as that by Holtgraves (2011) have shown that words that someone uses reliably indicate their personality characteristics. For this study, we used IBM Watson Personality Insights, a natural language processing-based tool similar to the LIWC sentiment dictionary, to infer the personality traits of each individual based on textual information shared at any time with others in the online health community (Yarkoni, 2010). For example, frequent use of first-person singular pronouns (e.g., ’I,’ ‘me’) is associated with higher neuroticism, while use of positive emotion words is linked to extraversion. This approach has been shown to reliably infer personality traits in online communication (Qiu et al., 2012).

3. Results

Using interaction data on (a) positive and negative advice ties and (b) patients’ expressed anxiety levels in their communications, we model network and behaviour changes at six points over 3 years. During the three years of data collected from a large English-speaking online health community, the patient network showed varying levels of anxiety expressed in written communication between peers. Many of the 200 individuals we observe are either awaiting or recovering from surgery, sharing treatment protocols and advice on day-to-day hurdles. Fig. 1 illustrates the advice ties, conveying positive or negative emotions, between 200 key individuals in an online support group focused on musculoskeletal pain at six points in time. The first graph (A) displays the network at the beginning of the data collection period, and each subsequent graph (B-F) shows the state of the network 6 months later than the previous graph. The nodes represent each of the 200 chosen actors. Node size represents each actor’s relative anxiety (0 = lowest, 5 = highest), and tie thickness corresponds to interaction frequency between two nodes. Anxiety is measured on a scale of 0 to 5, with 0 being the lowest and 5 the highest.

3.1. Descriptives

Table 3 presents means, standard deviations, ranges, and correlations between anxiety levels, the number of advice ties a person sends to peers, and the control variables. On average, anxiety decreased slightly during the 3-year period. However, there was a notable increase in the mean observed between Time 1 ($M = 0.81, SD = 1.42$) and Time 2 ($M = 1.46, SD = 1.59$), after which anxiety levels continued to decline until Time 6 ($M = 0.73, SD = 1.26$). On average, peers sent the majority of advice ties during the first three points in time (Time 1: $M = 14.10, SD = 16.25$, Time 2: $M = 18.89, SD = 23.60$, Time 3: $M = 14.63, SD = 19.98$), with the fewest ties sent during Time 6 ($M = 8.04, SD = 12.39$). High autocorrelations among the number of advice ties sent across all time points (ranging from 0.82 to 0.96) suggest that most users posted consistently throughout each observed period. The means of the control variables indicate that while, on average, many users used words associated with the personality traits ‘openness’ and ‘agreeableness’ ($M = 0.69, SD = 0.22$, and $M = 0.40, SD = 0.25$, respectively), much fewer users appear to be extroverted or neurotic ($M = 0.03, SD = 0.05$, and $M = 0.22, SD = 0.14$, respectively).

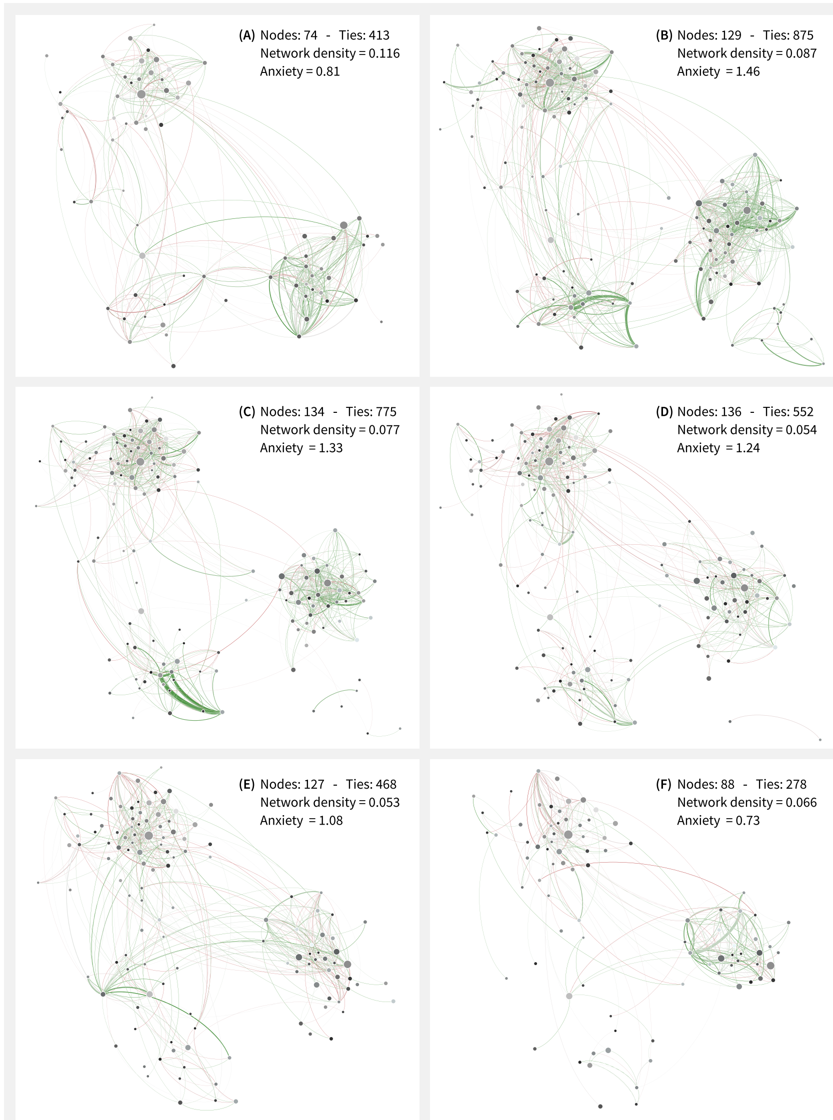


Fig. 1. Coevolution patterns of anxious attitude and network ties.
Notes. The first graph (A) displays the network at the beginning of the data collection period, and each sub- sequent graph (B–F) shows the state of the network 6 months later than the previous graph. The nodes rep- resent each of the 200 chosen actors. The size of each actor represents its anxious attitude, with larger circles indicating the use of more anxious words in the actor's communication with others. The thickness of the curved lines (directed ties) between two nodes indicates the frequency of contact. Anxious attitude is measured on a scale of 0 to 5, with 0 being the lowest and 5 the highest.

However, for the latter, it should be noted that the maximum values are 14, and 3 and a half times higher than the mean, respectively. This indicates the presence of outliers, namely a few individuals who scored high on extraversion or neuroticism.

3.2. Advice ties and anxiety

We predicted that advice ties and anxiety levels co-evolve as a function of five mechanisms: action (H_1), attraction (H_2), reaction (H_3), homophily (H_4) and assimilation (H_5). First, we focus on the results of the submodel shown in Table 4, where the advice ties are the dependent variable. The submodel shown in Table 5 presents the results of the coevolution of advice ties and anxiety levels with the latter as the dependent variable. Consequently, Table 4 includes the parameter estimates for action, attraction, and homophily (anxiety shapes advice ties), and Table 5 includes those for reaction and assimilation (advice ties shape anxiety).

Consistent with Hypothesis 1, more anxious individuals sent fewer advice ties to their peers, meaning that they responded to fewer of their peers' questions than those who were less anxious (action estimate, −0.23; p = .022). Hypothesis 2 was not supported; surprisingly, people with a more anxious attitude were not more likely to receive more advice from peers than people who, based on the words used in their request, appeared less anxious (attraction estimate, −0.16; p = .149). Instead, we note a slightly negative trend, although the effect did not reach two-sided statistical significance. Hypothesis 3 was not supported either; people who received more advice ties were not more likely to become less afraid than people who received fewer ties (reaction estimate, −0.01; p = .769). Contrary to Hypothesis 4, individuals sent more advice ties to peers whose anxiety levels were different from, rather than similar to, their own (homophily estimate, −0.85; p = .007). Finally, as predicted in Hypothesis 5, we found a significant assimilation effect (6.74; $p < 0.001$). Over time, individuals increasingly aligned their anxiety levels with those of their connected peers.

Table 4
SIENA estimation results (I): Coevolution of advice ties (DV) and anxiety levels.

Parameter	Estimate	S.E.	p		
Anxiety					
Action (sender)	−0.23	0.10	0.022	H_1	✔
Attraction (receiver)	−0.16	0.11	0.149	H_2	✘
Homophily (similarity)	−0.85	0.32	0.007	H_4	✘
Intercept					
Advice outdegree (density)	−3.26	0.17	<0.001		
Control variables: Network					
Advice reciprocity	1.67	0.55	0.002		
Advice transitivity	1.99	0.20	<0.001		
Advice cycles	−0.16	0.08	0.054		
Control variables: Person characteristics					
Extraversion (sender)	1.02	1.24	0.410		
Agreeableness (receiver)	0.28	0.15	0.064		
Neuroticism (sender)	1.85	0.34	<0.001		
Neuroticism (receiver)	−0.87	0.41	0.032		
Neuroticism (similarity)	0.62	0.17	<0.001		
Rate function					
Rate period 1 ($t_0 - T_1$)	144.66	44.05	0.001		
Rate period 2 ($t_1 - T_2$)	35.19	5.36	<0.001		
Rate period 3 ($t_2 - T_3$)	33.68	3.80	<0.001		
Rate period 4 ($t_3 - T_4$)	43.18	30.98	0.163		
Rate period 5 ($t_4 - T_5$)	16.09	2.97	<0.001		

Table 5
SIENA estimation results (II): Coevolution of advice ties and anxiety levels (DV)

Parameter	Estimate	S.E.	p		
Advice ties					
Reaction (receiver)	−0.01	0.04	0.769	H_3	✘
Assimilation (similarity)	6.74	1.90	<0.001	H_5	✔
Intercept					
Anxiety tendency	−0.78	0.28	0.006		
Anxiety tendency sq.	0.54	0.49	0.268		
Rate function					
Rate period 1 ($t_0 - T_1$)	30.57	20.52	0.136		
Rate period 2 ($t_1 - T_2$)	4.08	1.58	0.009		
Rate period 3 ($t_2 - T_3$)	4.35	1.29	0.001		
Rate period 4 ($t_3 - T_4$)	6.73	2.74	0.014		
Rate period 5 ($t_4 - T_5$)	4.35	1.12	<0.001		

3.3. Additional findings

To summarise, the results suggest that the anxiety levels of chronic pain patients and their online advice ties to peers coevolve as a function of action, heterophily, and assimilation (see Table 6 for a full overview). In addition, other interesting effects emerge from the control variables included in our analysis. First, individuals tend to respond to those who also responded earlier (homophily estimate, 1.67; $p = .002$). In addition, certain personality traits seem to affect the evolution of the network. Controlling for the effect of neuroticism, an individual's tendency to experience negative emotions such as anxiety, we found that although actors with higher levels of neuroticism communicated with more peers (neuroticism sender estimate, 1.85; $p < 0.001$), they were less likely to be selected (i.e., responded to) by others (neuroticism receiver estimate, −0.87; $p = .032$). Lastly, our analysis indicates that people tend to seek advice from others with similar levels of neuroticism (neuroticism similarity estimate, 0.62; $p < 0.001$).

4. Discussion

Choosing anxiety as a recognised precursor to chronic pain, we analysed three years of data on online interactions of patients with chronic pain, collected from a leading online health community. We analysed the coevolution of online advice ties and individuals' anxiety levels in two regards: how the receiver and sender of advice ties interact and how similar their anxiety levels are and become over time. By exploring the extent to which anxiety is socially contagious online, we responded to a recent call from Pagoto et al. (2019) to study the circumstances under which people benefit from being incorporated into health-related social networks. In support of previous findings (Zhao and Zhang, 2017), our results indicate that online health communities facilitate emotional exchanges that can partly mitigate anxiety. Furthermore, these platforms enable individuals to navigate complex emotions by seeking advice from both like-minded and diverse peers, as highlighted by Kostova et al. (2015) and Sillence (2010). Our findings also contribute to social network theory by demonstrating that **heterophily**, rather than homophily, drives advice-seeking behaviours in online health communities. This challenges traditional assumptions of network evolution and highlights the role of diverse emotional states in fostering meaningful social connections (Centola and van de Rijt, 2015; McPherson et al., 2001). Most prominently, we found a tendency for people to assimilate the anxiety of their peers, which is both concerning and encouraging, as it indicates that anxious individuals may "catch" the positive or negative attitude of their peers over time.

However, our results also indicate that people do not tend to cluster with others whose anxiety levels are similar to their own. This may

Table 6
Overview of hypotheses and results.

			Anxiety influences Network Ties	Network Ties influence Anxiety
Interaction	Sender [ego]	○⟶	H_1^- – *accepted:* More anxious individuals gave less advice	
	Receiver [alter]	⟶○	H_2^+ – *rejected:* Anxious users **did not** receive more advice than less anxious peers	H_3^- – *rejected:* Receiving more advice **did not** reduce subsequent anxiety
Similarity	Sender-receiver [dyad]	○⟷○	H_4^+ – *rejected:* Individuals formed more connections with peers who had **different anxiety levels** (heterophily)	H_5^+ – *accepted:* Anxiety levels converged over time

result in anxious individuals being less likely to build relationships with peers who are also anxious, which could otherwise lead to 'negative echo chambers' and instead connect with less anxious peers. This finding underscores the relevance of online health communities as a source of support for anxious individuals, as it can help them connect with a variety of peers who can offer helpful advice and perspective. From a practical standpoint, this suggests that OHC moderators or platform designers could focus more on encouraging diverse connections, ensuring that anxious users interact with those better equipped to provide reassurance or adaptive coping strategies.

Although social support would likely help anxious patients, we also found that more anxious individuals tend to form fewer advice ties, meaning that more anxious individuals could be more likely to be socially isolated. As a result, more anxious individuals may be less likely to benefit from the support available in online health communities. Furthermore, our findings highlight the need to consider personal differences due to certain personality traits when studying social network changes, as they have significant implications for both network formation and network functioning. In particular, neuroticism and extraversion are important personality traits to consider, as they likely influence how people connect within social networks. For example, users high in neuroticism formed more ties overall yet were less frequently chosen by others, suggesting a more complex dynamic where they actively reach out yet may not consistently receive a response.

In summary, our study confirms the importance of understanding anxiety in an online health context, as well as the need for more research on how anxious individuals can be supported by others online. While anxious individuals exhibit a tendency toward social isolation, our findings suggest that those with contrasting anxiety levels interact more frequently, fostering diverse connections. This 'opposites attract' dynamic highlights the potential of OHCs to bridge emotional gaps through peer support. Personality traits such as neuroticism further affect these dynamics, influencing how users seek and respond to support (Zeng et al., 2016; Gosling et al., 2003). Taken together, these insights add to knowledge about network evolution (e.g., Centola and van de Rijt (2015)) by emphasising how specific emotional states and individual difference variables shape the formation, maintenance, and effect of online connections.

Studies such as ours are an important step towards identifying ways to address social isolation or exclusion among vulnerable and anxious individuals, such as patients with chronic or stigmatising conditions (Kostova et al., 2015). By concentrating on the 200 most active participants, we captured the core mechanisms of social and emotional exchange, which are less likely to emerge among less engaged users. However, this approach limits the generalisability of our findings to the broader community. Future research might examine how the same mechanisms might manifest among more peripheral participants, who could be reluctant to seek help or who lack the time and resources to interact regularly. Furthermore, more research is needed to explore the effects of negative attitudes on online interactions, including whether anxious individuals are more likely to build or refrain from relationships with particular peers. In addition, additional studies are needed to fully understand whether and how anxious individuals might overcome their anxiety through the support of others online. Lastly, future work might also focus on a different group of patients, i.e. those suffering from conditions where less is known about the mediating effect of social support in the relationship between anxiety and health outcomes.

5. Conclusions

By integrating insights from social network theory and online health communication research, this study advances a nuanced understanding of emotional contagion and heterophily in online health communities. We believe that our study provides valuable information on how patients discuss chronic pain conditions online and seek support from others who experience similar problems. More specifically, the observed mechanisms of "action" (anxious individuals sending fewer ties), "heterophily" (connecting with peers who differ in anxiety), and "assimilation" (adopting peers' anxiety over time) show a distinctive pattern in how emotional states affect online interactions. As such, we hope that our findings will contribute to a better understanding of the role of online health communities in helping anxious individuals overcome their fears and find support among their peers. Ultimately, by better understanding the social dynamics surrounding anxiety and chronic pain, we hope to inform future interventions that can help anxious individuals connect with others and feel less isolated from those around them. Based on our findings, we propose several concrete intervention strategies for future application. First, a dynamic buddy system could be implemented in online health communities to pair users based on complementary anxiety levels. Our findings show that highly anxious individuals tend to send fewer advice ties. Therefore, by periodically re-assessing users' emotional profiles and re-pairing those with high anxiety with peers with lower anxiety, an OHC could foster more balanced support and reduce isolation. Second, to avoid over-reliance on a small number of superusers and to reduce the risks associated with concentrated influence and potential misinformation being spread by a few influential users, we recommend promoting relational multiplexity. In practice, this means encouraging users to engage with multiple peers rather than depending on a single, highly influential user. Third, the use of network and sentiment analysis could help identify users who are increasingly isolated or showing signs of emotional distress. Alerts based on these analyses could notify moderators to intervene promptly, ensuring timely support. Finally, integrating AI-driven moderation tools to continuously monitor peer discussions and flag escalating conversations could help safeguard the community by preventing potentially anxiety-inducing exchanges.

Table A.1
Comparison of superusers and all users on important activity metrics.

Metric	Superusers	All users
Replies sent	17.63 (113.05)	9.01 (49.95)
Words per post	108.00 (109.71)	107.62 (104.50)
Threads started	17.71 (18.45)	2.27 (25.07)
Replies received	8.87 (34.77)	9.48 (21.89)
Likes per reply	0.59 (2.45)	0.46 (1.64)
Tenure (days)	902.94 (396.59)	748.90 (505.51)

Notes. "Replies sent" is the mean number of replies authored. "Words per post" is the mean word count per reply. "Threads started" is the mean number of unique discussion threads initiated by each user. "Replies received" is the mean number of replies each user received for their initiated threads. "Likes per reply" is the mean number of likes received per reply. "Tenure (days)" is the mean number of days since the account was created.

CRediT authorship contribution statement

Jasmina Rueger: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Wilfred Dolfsma:** Writing – review & editing, Writing – original draft, Validation, Supervision, Conceptualization. **Rick Aalbers:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly in order to enhance readability and grammatical correctness. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no competing interests.

Appendix. Supplementary analyses

See Table A.1.

Data availability

Data will be made available on request.

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