Online Supplement to Ripples of Emotion: Unraveling the Dynamics of Emotion Flows and User Engagement in Online Healthcare Communities

Tongxin Zhou
W. P. Carey School of Business, Arizona State University, tongxin.zhou@asu.edu

Jingyi Sun
School of Business, Stevens Institute of Technology, jsun54@stevens.edu

A1. Detection of Post Target Users

The focal platform has integrated a citation function designed to facilitate direct connections among users. This function allows users to explicitly address their responses to specific individuals by tagging each other's usernames or quoting specific content for commentary. This feature enhances direct and visible interactions among users, which enables us to trace the conversation structure within forum discussions with greater accuracy. Leveraging the capabilities of the citation function, we have implemented the following procedure to analyze communication events: 1) For the tagged or quoted comments, we identified instances where users directly mentioned others' usernames as well as instances where users quoted parts of previous posts. This helped us understand how users reference each other to indicate a direct engagement with specific users, statements, or ideas. 2) We also considered implicit mentions where a user might mention another's username without using the '@' function. This might signify an intention to engage with that specific individual. Similarly, we also identify cases where users mention a previous post without quoting, by detecting overlaps between text contents. 3) For posts that did not include any of the above explicit or implicit citations, we employed a heuristic approach based on the structure of the conversation. If the author of a post was not the initial thread creator, we assumed the post was directed at the initiator. If the author was the thread creator, we assumed the reply was directed at the most recent comment in the thread. We adopt alternative ways to construct the reply network in robustness checks.

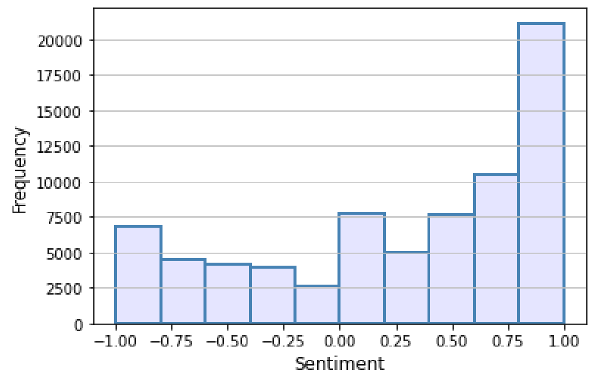

Figure A1 **Distribution of the Sentiment Scores**

A2. Illustration of Forum Posts

Figure A1 shows the distribution of the sentiment scores. While the majority of posts exhibit positive sentiments—often seen when users welcome each other, celebrate milestones, or offer encouragement—a significant portion of reply messages manifest negative sentiments. These negative sentiments typically emerge when individuals express loneliness, frustration, distress, or dissatisfaction regarding personal experiences, or when engaging in sensitive topics that lead to expressions of disagreement. In Table A1, we present a selection of forum posts from the focal community to illustrate the range of emotions expressed by its members. These examples serve as a qualitative snapshot of the emotional landscape within the community. For negative emotions, users frequently express feelings such as fear, frustration, anger, criticism, and dissatisfaction. On the other hand, positive emotions commonly manifest as expressions of hope, joy/happiness, and friendliness.

To offer a more comprehensive view of the community's emotional landscape, we employ NRCLex, a lexicon-based emotion classifier. NRCLex allows us to categorize the emotions expressed in forum posts into specific labels, including sadness, fear, disgust, anger, trust, surprise, joy, and anticipation. Figure A2 shows that the most frequent emotion that the community members expressed was trust, followed by anticipation, fear, joy, and sadness. Figure A3 visualizes the emotion dynamics of the online healthcare community. Positive replies are shown in pink and negative replies are shown in purple. Some dyads repeatedly experience negative emotions, and there is some local clustering of negative emotions, but overall replies are more positive than negative.

Table A1 Examples of Emotions Expressed in the Forum Posts

Post	Type of Emotion	Sentiment
For the fear of knowing what it is and hearing a time limit. I'm on ART but my memory is so bad i miss at least 2 days a week. I'm sure I'm resistant. I have No one here and I am Paralyzed in fear.	Fear	Negative
I don't believe the laws to be reasonable... If they were so worried about spreading disease, then they would screen people for said diseases and provide prevention information that was based on science and not religious dogma.	Frustration/Criticism	Negative
Good lord... whats with all the self loathing posts as of late..... the whole finger pointing attitude needs to stop.. Gosh, this is as dumb a poll as I ever saw.	Dissatisfaction	Negative
Hello ***, and welcome back. It is good to hear that you now have things under control and you are doing much better. Eat, eat, and eat, drink plenty of fluids, and get plenty of rest also.	Encouragement	Positive
Wow! Thanks very much for the warm welcome! Getting rid of the illusion of "alone-ness", which I know that is what it is, an illusion, makes a big difference.	Hope	Positive
Hi ***, I used to be a desert rat too... but had to escape to cooler temps! Congrats on the sobriety and the stopping smoking. I think you'll find many people here that can help you with some of your questions. Glad you were able to make it here.	Empathy	Positive

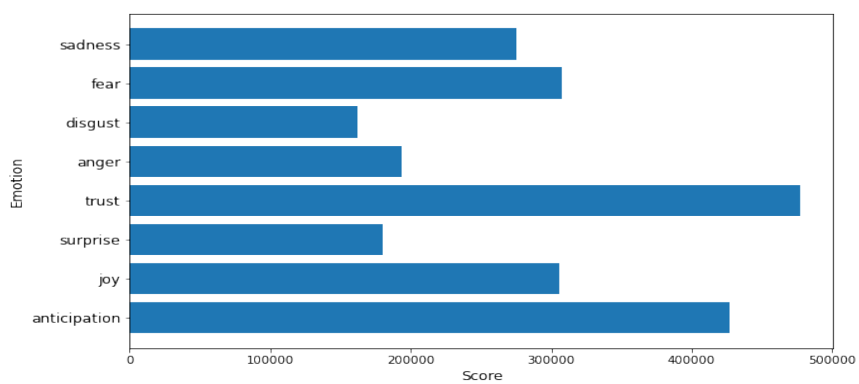

Figure A2 Overall Emotion Categories in the Forum Discussions

A3. Topic Modeling of Posts

We conduct topic modeling to examine the content of posts. The topics of posts serve two purposes. First, we rely on topic detection to understand the nature of emotional exchanges on the focal platform. Second, we rely on topic detection to control for topic homophily in our main models of

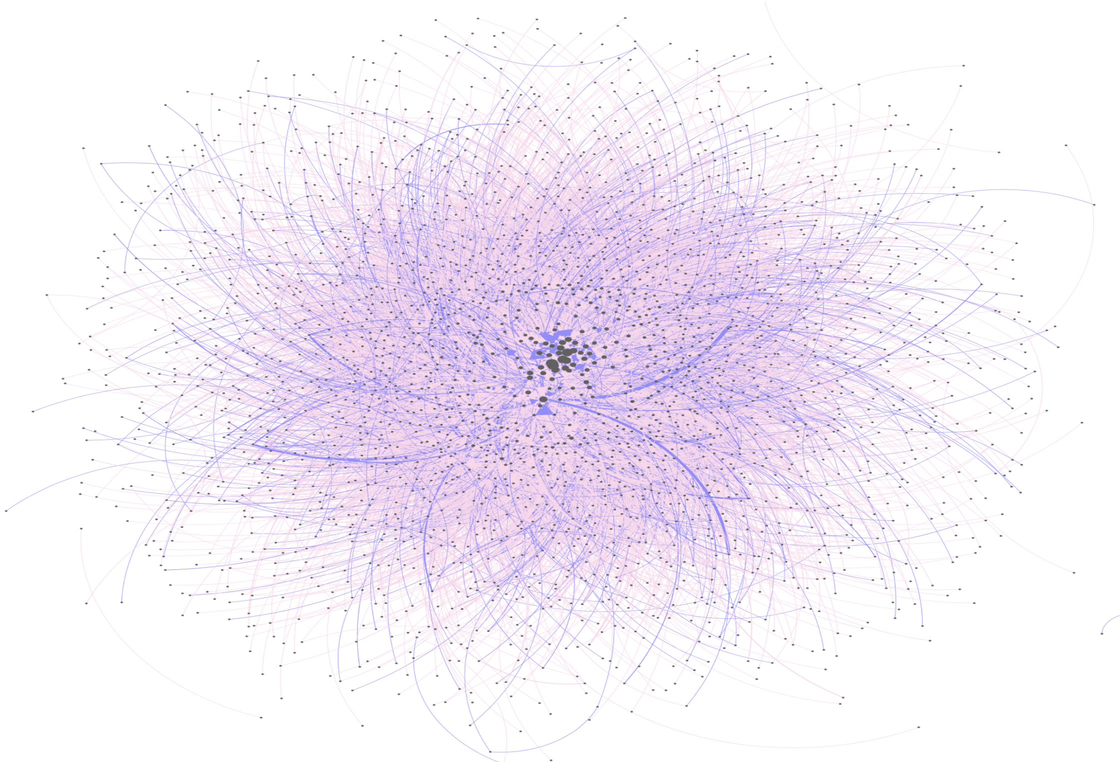

Figure A3 Visualization of Positive and Negative Replies in Health Forum Discussions

emotion flows. That is, our findings regarding Emotional Resonance Cascade (ERC) and Emotional Feedback Exchange (EFE) are different from similar emotional tendencies towards the same topics.

Before modeling, we preprocess the text of all posts in the following steps using *stanza* package. First, we split each post into sentences and conduct Named Entity Recognition (NER) to remove named entities such as persons, organizations, times, and locations. In topic modeling, excluding named entities may allow a fair emergence of topics from different sources. Second, we perform Lemmatization to normalize words, where words are replaced by their base forms. Third, we extract phrases from the text because some combinations of single words may deliver special meanings. We perform Dependency Parsing to extract collocations. Dependency parsing is the process of analyzing the grammatical structure of a sentence and examining the relationship between words. If the relationship between two words is identified as “compound,” it shows that these words usually have special meanings when they appear together. Compounds are extracted and glued with a hyphen, e.g., “blood-donation,” “therapy-appointment,” and “support-group.” To further detect phrases, we remove emojis, punctuation, and stop words, and use the *phraser* module from the *genism* library to detect collocations and combine them with "_". Collocations are phrases that may capture special meanings in our corpus, e.g., "viremic_controller," "anti_depressant," and "suicidal_ideation." Compounds and collocations combined may capture some phrases specific to the current context, e.g., "flexible_spending-account." The cleaned sentences are aggregated back to the post level.

After preprocessing, we perform the Latent Dirichlet Allocation (LDA) algorithm. Since it is unknown how many topics may emerge from the corpus, we iterate over the number of topics to calculate the perplexity score. As shown in Figure A4, the increase of perplexity flattens around 20 topics, indicating this model is the best. Table A2 shows the topics and associated keywords. Each cleaned post is assigned to a topic with the highest probability.

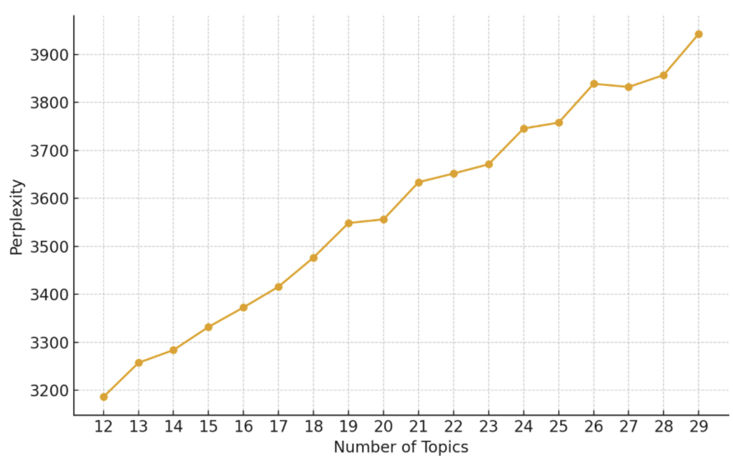

Figure A4 Perplexity for Topic Number Diagnostics

A4. The Scope of Emotional Transmissions

We did the following tests to ensure the construct validity *Indegree_Source* for ERC and *Outdegree_Target* for EFE. These two measures are not the same as or constrained by structural homophily and semantic homophily.

First, we examine how *Indegree_Source* and *Outdegree_Target* variables measure interactions confined by local clusters. Starting from the second month (February 2010), for each event

Table A2 Detection of the Number of Topics for Topic Modeling

Topic index	Topic label	Keywords
0	Food	eat, drink, food, water, good, like, use, make, diet, also, try, oil, fish, lot
1	Health check	cd, count, test, number, vl, result, start, med, lab, go, viral_load, undetectable
2	Sex	hiv, sex, person, know, risk, would, partner, condom, get, poz, infect, positive
3	Sex	man, gay, like, woman, love, mtd, see, think, say, old, one, young, know
4	Gratitude	million, know, thanks, get, think, post, say, like, want, go, read, thank
5	Daily life	take, get, feel, go, day, like, pain, time, sleep, night, good, bad, million
6	Treatment	doctor, get, go, ask, tell, see, doc, say, would, hiv, know, call, hospital, test
7	Daily life	get, go, back, time, million, day, come, like, home, think, say, work
8	Treatment	cause, surgery, infection, doctor, cancer, test, liver, problem, blood, treatment
9	Forum	person, think, make, would, say, post, one, forum, thread, many, point, see
10	Support group	help, group, support, work, find, good, hiv, person, need, also, live, get
11	News	http_www, article, hiv, com, link, aid, aids, health, say, state, news, org, site
12	Insurance	pay, insurance, company, cost, would, work, health, money, med, plan, drug
13	Daily life	miss, one, use, name, pill, look, lol, box, put, bottle, wear, yes, like, picture
14	Mood	good, hope, great, well, hear, glad, love, happy, wish, keep, day, sorry, hug,
15	Law	hiv, law, country, none, person, state, status, case, travel, legal, know, ban
16	Treatment	med, effect, start, side, good, time, think, day, work, million, get, doctor
17	Research	study, drug, treatment, resistance, virus, cell, risk, therapy, infection, research
18	Treatment	hiv, aid, live, die, disease, get, virus, life, many, year, treatment, cure, death
19	Daily life	life, know, feel, think, good, time, tell, go, like, get, make, person, want, friend

between a pair of sender and receiver at a time point, we calculate from whom the current sender has received positive and negative replies in the past month (this is roughly equivalent to $Positive/Negative\_Indegree\_Source$ variables in the REM), and to whom the receiver sent replies (this is roughly equivalent to $Positive/Negative\_Outdegree\_Target$ variables in the REM). The difference is that, instead of simply aggregating relational events sent or received previously, we identify the individuals involved in those interactions.

Meanwhile, for all the events that happened in the previous month, we build a cross-sectional network and conduct community detection. Community detection refers to the process of identifying local clusters in a network, where ties have a higher chance of falling into clusters than falling between clusters. We use the walktrap algorithm. The walktrap algorithm starts from a partition into n communities reduced to a single vertex. Then it computes the distance between all adjacent vertices based on random walks in order to choose two communities and merge them into a new community. The distance measures are iteratively updated to generate new communities. The algorithm returns the identification of various communities in a network and assigns each node to one of these communities. With the membership information, we can identify whether the individuals who previously interacted with the current source nodes or current target nodes are from the same communities as them.

For $Indegree\_Source$, the current sources on average have received positive messages from individuals embedded in 11.96 local communities ($SD = 15.21$), and on average 48% ($SD = 0.30$) of these individuals are NOT from the same communities as the current source. Meanwhile, the current sources on average have received negative messages from individuals embedded in 5.77 communities ($SD = 8.78$), and on average 47% ($SD = 0.35$) of these individuals are NOT from the same communities as the current source.

For $Outdegree\_Target$, the current targets on average have sent positive messages to individuals embedded in 12.42 local communities ($SD = 14.13$), and on average 49% ($SD = 0.30$) of these individuals are NOT from the same communities as the current target. The current targets on average have sent positive messages to individuals embedded in 6.12 local communities ($SD = 8.28$), and on average 47% ($SD = 0.34$) of these individuals are NOT from the same communities as the current target.

To summarize, $Indegree\_Source$ and $Outdegree\_Target$ can capture previous interactions with others from different social clusters. Around half of the current sources and targets are not in the same communities as prior interactions. The proposed mechanisms can cover a wide range of emotional exposure in the broad community rather than local clustering. Hence, our findings can illustrate that people indeed transmit emotions outside their immediate social circles.

Second, we examine how $Indegree\_Source$ and $Outdegree\_Target$ variables measure interactions that are not confined by threads. Threads about specific topics may instigate certain emotions and create social norms for complying with dominant emotions. Hence, we examine to what extent $Indegree\_Source$ and $Outdegree\_Target$ variables overlap with the clustering under the same threads. Related to $Indegree\_Source$, for each observed event in the sequence, within a sliding window of one month, we calculate the number of threads within which the current source has previously received positive/negative messages, along with the entropy of the distribution of such messages. A larger entropy means that a sender has previously interacted with a wide range of threads rather than focusing on a few threads. Similarly, related to $Outdegree\_Target$, we calculate the number of threads within which the current target has previously sent positive/negative messages and the entropy of message distribution in threads.

For $Indegree\_Source$, the current sources on average have previously received positive messages within 6.16 threads ($SD = 6.86$) and negative messages within 3.61 threads ($SD = 4.68$). The average entropy is 1.73 for positive messages and 1.44 for negative messages. Along the entire sequence, in 64.98% of the events, the current threads within which the current sources send messages are NOT the same as the threads within which they have received messages in the past month.

For $Outdegree\_Target$, the current targets on average have previously sent positive messages within 8.15 threads ($SD = 8.50$) and sent negative messages within 4.36 threads ($SD = 5.43$). The average entropy is 2.10 for positive messages and 1.36 for negative messages. Along the entire sequence, in 20.78% of the events, the current threads within which the current targets receive messages are NOT the same as the threads within which they have sent messages in the past month.

To summarize, both $Indegree\_Source$ and $Outdegree\_Target$ capture emotional interaction in multiple threads. Specifically, $Indegree\_Source$ captures users' emotional exposure within a wide range of threads, which is likely to transmit emotional expressions in different threads. $Outdegree\_Target$ also captures users' emotional expressions in a wide range of threads, which may also lead to emotional feedback in different threads. By comparison, EFE is more constrained by threads whereas ERC is more likely to traverse threads.

Third, we examine how $Indegree\_Source$ and $Outdegree\_Target$ variables measure interactions that are not confined by topics. Based on the topic modeling, each reply event is assigned to a topic with the highest probability. Following the same approach, related to $Indegree\_Source$, for each observed event in the sequence, within a sliding window of one month, we calculate the number of topics within which the current source has previously received positive/negative messages, along with the entropy of the distribution of such messages. We do the same for all receivers in the sequence related to $Outdegree\_Target$.

For $Indegree\_Source$, the current sources on average have previously received positive messages about 5.71 topics ($SD = 4.92$) and negative messages about 3.40 topics ($SD = 3.76$). The average entropy is 1.83 for positive messages and 1.21 for negative messages. Along the entire sequence, in 50.70% of the events, the current topics about which the current sources send messages are NOT the same as the topics about which they have received messages in the past month.

For $Outdegree\_Target$, the current targets on average have previously sent positive messages about 6.04 topics ($SD = 5.04$) and sent negative messages about 3.61 topics ($SD = 3.84$). The average entropy is 1.90 for positive messages and 1.27 for negative messages. Along the entire sequence, in 42.66% of the events, the current topics about which the current targets receive messages are NOT the same as the topics about which they have sent messages in the past month.

To summarize, both $Indegree\_Source$ and $Outdegree\_Target$ capture emotional interactions spanning multiple topics. $Indegree\_Source$ reflects prior emotional exposure across diverse topics, and for half the amount of times source nodes switch topics when spreading emotions to others. $Outdegree\_Target$ captures prior emotional expressions across multiple topics, many of which differ from the topics currently received by targets.

A5. Selection of Time Decay Parameter for REM

We follow a model selection process to choose the optimal time decay parameter for REM. Previous research has shown that model fit can be an important criterion for selecting model specification (Schecter et al. 2018). We follow a data-driven approach to iterate the time decay parameter from 1 week to 8 weeks and examine the corresponding changes in model fit criteria such as AIC. For each time decay parameter, we calculate the network variables and estimate the AIC for positive models and negative models, because conditional models with different time decay values do not see much change in AIC. Figure A5 shows how the average AIC of positive models and negative models changes as the time decay weeks increase. As illustrated, the time decay of four weeks seems to be the best option.

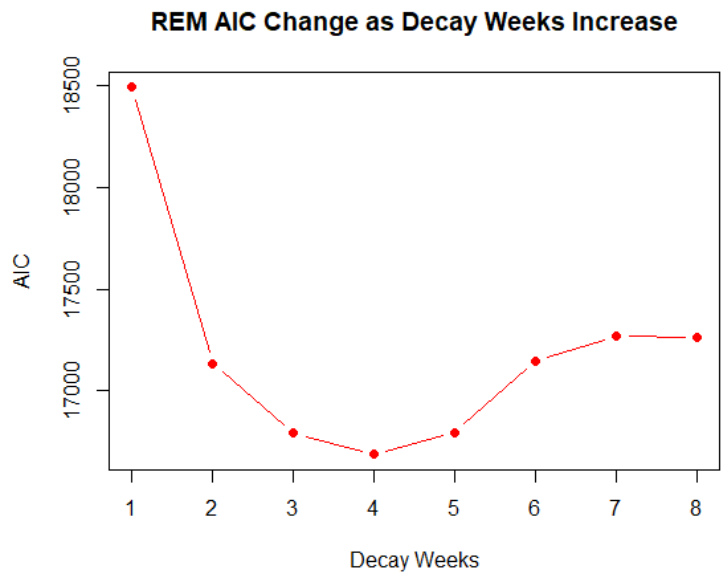

Figure A5 **Selection of Time Decay Parameter for REM**

A6. Prompt for LLM-based Content Extraction

The prompt used for LLM-based content extraction is as follows:

"In online healthcare forums, sentiments can generally be classified into two categories:

1. Disease-related – These sentences discuss medical conditions, symptoms, treatments, or medications. Examples: "I have been experiencing headaches since starting this medication."

2. Emotion/Feelings-related – These sentences express personal emotions, moods, or appreciation. Examples: "I always feel bad"; "I'm happy"; "Thank you so much for your support."

Please separate all the sentences in the given text into these two categories. Strictly follow the below output format:

Disease: the disease-related sentences

Feelings: the emotions/feelings-related sentences

Note: Please put the original sentences. If there are no relevant sentences in a category, write "No".

"

Table A3 Description of Control Variables

Control Variable	Description	Measurement Aspect
ave_sentiment_source/ ave_sentiment_target	The average sentiment of the posts published by the source/target user during the last 30 days	The overall emotion and/or mental health of the source/target user during the recent period
ave_length_source/ ave_length_target	The average post length of the source/target user during the last 30 days	The activity level of the source/target user during the recent period
member_target/	Whether the source/target user is a member (member=1, administrator=0)	The impact brought by community roles
ave_sentiment_diff	The difference in the average sentiment of the source user and the target user during the last 30 days	The emotion similarity between the source user and the target user
embedding_sim	The similarity in word embeddings (1-cosine similarity) between posts from the source and target users during the last 30 days	The similarity in users' post contents
topic_sim	The similarity in the topic distributions of the source user and the target user during the last 30 days	The similarity in participation interests between the source user and the target user
current_thread_init_sentiment	The sentiment of the initial post in the current thread	The influence of the initial post's sentiment on subsequent replies within the thread
source_init_sentiment	The average sentiment of initial posts recently made by the source user	The influence of the sentiment of the source user's initial posts on subsequent replies received by the source user
target_thread_init_sentiment	The average sentiment of initial posts in threads where a target user has previously replied	How the target user's replies in threads are influenced by the initial posts of those threads

A7. Description of Additional Control Variables

In addition to network controls, our study incorporates additional actor- and dyad-level control variables to account for individual heterogeneity and tie-formation tendencies. Table A3 provides a detailed description of these control variables and their measurement aspects.

A8. Descriptive Statistics of the Variables

In Table A4, we provide the descriptive statistics of the variables as well as their correlation matrix.

A9. Results on Network Control Variables

Our REM models also provide estimates for the impact of other network variables, such as those regarding the dyadic, degree, and triadic mechanisms, as illustrated in Table 2 in the main paper. First, our findings suggest a repetition pattern at the dyad level ($Positive\_Repetition$ and $Negative\_Repetition$). That is, if an individual has previously conveyed a message with either a positive or negative sentiment to a particular person, they are more likely to continue to send messages to the same person. Conditional on an interaction, individuals who have sent negative emotions are less likely to express positive sentiment to the same recipient. Moreover, after sending

Table A4 Descriptive Statistics of Network and Control Variables

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Positive_Repetition	10.64	12.53																									
Negative_Repetition	4.94	6.90	.92																								
Positive_Reciprocation	10.70	11.26	.11	.12																							
Negative_Reciprocation	5.22	6.75	.12	.13	.88																						
Positive_Outegree_Source	.34	.68	.32	.29	.38	.37																					
Negative_Outegree_Source	.18	.47	.31	.33	.35	.40	.52																				
Positive_Indegree_Source	.32	.65	.40	.35	.39	.32	.55	.42																			
Negative_Indegree_Source	.17	.45	.37	.42	.33	.40	.43	.52	.46																		
Positive_Outdegree_Target	11.66	11.27	.80	.74	.12	.13	.40	.34	.30	.29																	
Negative_Outdegree_Target	5.63	6.65	.79	.83	.12	.14	.34	.41	.29	.33	.87																
Positive_Indegree_Target	11.67	13.68	.11	.11	.86	.85	.45	.40	.31	.31	.13	.13															
Negative_Indegree_Target	5.47	7.64	.11	.12	.79	.88	.41	.46	.28	.34	.13	.15	.93														
Positive_Positive	9.95	21.21	.55	.53	.58	.57	.56	.54	.52	.52	.54	.53	.59	.57													
Positive_Negative	5.35	13.41	.53	.59	.51	.51	.50	.55	.48	.53	.51	.58	.52	.50	.92												
Negative_Positive	5.42	13.64	.49	.47	.54	.62	.52	.55	.47	.52	.48	.47	.57	.62	.93	.85											
Negative_Negative	3.23	9.22	.48	.53	.48	.56	.48	.56	.45	.54	.46	.53	.50	.55	.86	.92	.92										
Avg_length_source	35.98	61.24	.24	.21	.04	.04	.11	.10	.10	.09	.26	.26	.04	.04	.15	.14	.13	.13									
Avg_length_target	34.54	58.38	.03	.03	.30	.27	.13	.10	.13	.10	.03	.04	.27	.24	.17	.15	.16	.15	.02								
Avg_sentiment_diff	.14	.20	.04	-.01	.07	-.02	.04	-.02	.05	-.02	.05	-.03	.04	.00	.03	.00	.00	-.02	.37	.38							
Avg_sentiment_source	.08	.17	.13	.05	.01	.01	.08	.00	.08	.02	.16	.01	.02	.01	.08	.02	.07	.02	.56	.01	.54						
Avg_sentiment_target	.08	.17	.00	.00	.18	.02	.07	.02	.09	.00	.00	.00	.13	.05	.08	.08	.02	.02	.01	.57	.53	.01					
Embedding_sim	.60	.47	.20	.19	.38	.33	.24	.21	.21	.19	.25	.22	.34	.30	.31	.27	.27	.24	.18	.26	.18	.13	.19				
Topic_sim	.32	.27	.28	.26	.44	.40	.39	.34	.35	.31	.34	.32	.39	.36	.44	.40	.40	.37	.14	.18	.08	.08	.11	.49			
Current_thread_init_sentiment	.16	.73	-.02	-.04	-.02	-.05	-.02	-.04	-.01	-.05	-.02	-.04	-.02	-.05	-.03	-.04	-.04	-.04	.00	.01	.03	.03	.04	-.03	-.03		
Source_init_sentiment	.09	.45	.08	.03	.01	.00	.03	.00	.06	.01	.04	.00	.00	.00	.04	.00	.03	.00	.09	.00	.10	.19	.00	-.01	.03	.20	
Target_thread_init_sentiment	.16	.37	-.02	-.02	.04	-.02	.00	-.03	.02	-.02	-.02	-.03	.02	-.03	.00	.00	-.02	-.02	.00	.03	.06	.02	.11	.05	.04	.43	.10

a message of a given emotional tone, the probability of receiving both positive and negative replies from the same recipient increases ($Positive\_Reciprocation$ and $Negative\_Reciprocation$). However, if a reply is received, it is more likely to align with the sentiment of the initial message sent. As explained in the identification strategy, such dyadic mechanisms control for instances where users repeat future emotional interactions with old acquaintances. Consequently, the cascade and exchange mechanisms in question estimate the extent to which past emotional interactions can influence future emotional interactions with different people.

Second, at the "degree level," we find that individuals who have historically sent many positive messages often continue to send more messages in general ($Positive\_Outdegree\_Source$). Those who have frequently sent negative messages are likely to continue sending negative messages in the future ($Negative\_Outdegree\_Source$). Furthermore, when an individual has a history of receiving messages with a specific emotional tone, they are more likely to continue receiving messages in that same sentiment from the wider community ($Positive\_Indegree\_Target$ and $Negative\_Indegree\_Target$). These patterns may occur due to community reinforcement, social expectations, or the individual's role within the community, which collectively act as magnets for similar emotional interactions. Controlling for these degree mechanisms accounts for observable heterogeneity in sending and receiving specific emotional valence.

Finally, our results show that users' emotions can be transferred via triadic relationships. For instance, if user A and user C share a positive interaction, but user C's interaction with user B is negative ($Positive\_Negative$), user A becomes less inclined to engage with user B. Such reluctance may arise from the mixed emotional cues indirectly conveyed through user C, causing emotional incongruity and hesitancy. Similarly, if user A communicates negatively with user C, and user C engages positively with user B ($Negative\_Positive$), user A also becomes less likely to engage with user B. In scenarios where both user A and user B engage in negative communication with user C ($Negative\_Negative$), the likelihood for user A to connect with user B increases, and the reply from A to B is more likely to be positive if there is a reply. In this case, the uniform negativity could act as a form of social glue (e.g., "enemy's enemy is a friend"). Controlling for these triadic mechanisms further accounts for complex clustering in small groups. Hence, the cascade and exchange mechanisms in question are not attributed to structural clustering, where emotional homophily, incongruency, or even conflicts may arise in small groups.

A10. Robustness-Check Results

A10.1. Different Threshold for Sentiments

In the main analysis, we classify replies with sentiment scores above 0 as positive and those with scores of 0 or below as negative. We apply different thresholds to categorize sentiments to test robustness. Specifically, we focus on more extreme sentiment values by using the 30th and 70th percentiles of the sentiment score distribution: replies in the bottom 30% are classified as negative, those in the top 30% as positive, and the remaining replies as neutral. The neutral replies are not counted when calculating network statistics. Our results are reported in Table A5.

A10.2. Alternative Heuristic to Construct the Reply Network

In our main analysis, we use the citation function to identify targeted users. When no explicit or implicit citation is present, we apply a heuristic approach. For this robustness check, we construct the network using an alternative method. Specifically, we adopt the following heuristics: (a) If

Table A5 Robustness Check 1: Different Threshold for Sentiments

	(1)	(2)	(3)
Dependent Variable	Positive	Negative	Is_Positive
Specification	Marginal	Marginal	Conditional
Positive Indegree Source	0.258***	0.158**	0.070***
	(0.039)	(0.068)	(0.026)
Negative Indegree Source	-0.113***	0.015	-0.065**
	(0.043)	(0.077)	(0.030)
Positive Outdegree Target	0.321***	0.218***	0.089***
	(0.032)	(0.054)	(0.019)
Negative Outdegree Target	-0.295***	-0.145**	-0.153***
	(0.037)	(0.067)	(0.025)
Network Controls			
Positive Repetition	0.204***	0.227***	0.008
	(0.028)	(0.051)	(0.011)
Negative Repetition	0.347***	0.354***	-0.022*
	(0.034)	(0.065)	(0.011)
Positive Reciprocation	0.378***	0.257***	0.063***
	(0.028)	(0.045)	(0.011)
Negative Reciprocation	0.286***	0.482***	-0.122***
	(0.034)	(0.060)	(0.011)
Positive Outdegree Source	0.327***	0.288***	0.009
	(0.035)	(0.059)	(0.023)
Negative Outdegree Source	0.149***	0.220***	-0.024
	(0.042)	(0.076)	(0.029)
Positive Indegree Target	0.749***	0.578***	0.077***
	(0.039)	(0.070)	(0.024)
Negative Indegree Target	0.109***	0.376***	-0.096***
	(0.042)	(0.078)	(0.027)
Positive-Positive	-0.103*	0.075	0.032
	(0.062)	(0.118)	(0.026)
Positive-Negative	-0.047	-0.228	-0.043*
	(0.064)	(0.139)	(0.026)
Negative-Positive	-0.220***	-0.357***	-0.022
	(0.060)	(0.126)	(0.027)
Negative-Negative	-0.097	0.024	0.097***
	(0.069)	(0.145)	(0.027)
Other Controls	yes	yes	yes
AIC	22,594	8,523	77,467

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors are reported in parenthesis.

the post author is not the thread initiator, we assume the reply is directed at the author of the immediately preceding reply. (b) If the post author is the thread initiator, we assume the reply is directed at all prior replies within the thread. This alternative approach allows us to assess the sensitivity of our findings to different assumptions about reply targeting. Our results are reported in Table A6. The findings show recent positive interactions drive engagement in reply activities whereas recent negative interactions suppress such engagement. These findings align with the main findings on mental-resource-driven emotion flows.

A10.3. Rely on No Heuristic to Construct the Reply Network

In this robustness check, we reconstruct the reply network using only events where a target is explicitly or implicitly mentioned. This approach enables us to build the network without relying

Table A6 Robustness Check 2: Alternative Heuristic to Construct the Reply Network

	(1)	(2)	(3)
Dependent Variable	Positive	Negative	Is_Positive
Specification	Marginal	Marginal	Conditional
Positive Indegree Source	0.217***	0.306***	0.038
	(0.048)	(0.089)	(0.037)
Negative Indegree Source	-0.197***	-0.110	-0.067*
	(0.044)	(0.080)	(0.035)
Positive Outdegree Target	0.460***	0.207***	0.178***
	(0.033)	(0.066)	(0.027)
Negative Outdegree Target	-0.217***	-0.146**	-0.188***
	(0.032)	(0.065)	(0.027)
Network Controls			
Positive Repetition	0.103***	0.224***	0.005
	(0.022)	(0.048)	(0.013)
Negative Repetition	0.087***	0.251***	-0.024**
	(0.022)	(0.050)	(0.012)
Positive Reciprocation	0.195***	0.103***	0.076***
	(0.017)	(0.037)	(0.012)
Negative Reciprocation	0.118***	0.274***	-0.127***
	(0.018)	(0.044)	(0.012)
Positive Outdegree Source	0.495***	0.412***	0.039
	(0.043)	(0.079)	(0.031)
Negative Outdegree Source	0.086**	0.178**	-0.035
	(0.042)	(0.075)	(0.032)
Positive Indegree Target	0.397***	0.783***	0.041
	(0.041)	(0.087)	(0.033)
Negative Indegree Target	0.110***	0.104	-0.119***
	(0.039)	(0.080)	(0.032)
Positive-Positive	-0.415***	-1.065***	0.058
	(0.068)	(0.163)	(0.047)
Positive-Negative	-0.035	0.317**	-0.038
	(0.059)	(0.150)	(0.043)
Negative-Positive	-0.059	0.436***	-0.063
	(0.057)	(0.160)	(0.042)
Negative-Negative	0.001	-0.262*	0.100**
	(0.053)	(0.152)	(0.039)
Other Controls	yes	yes	yes
AIC	26,470	9,107	76,811

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors are reported in parentheses.

on heuristics to infer reply targets. The results, reported in Table A7, are similarly consistent with our main findings.

A10.4. Control for Short-Term Emotional Interactions

To assess whether our main results are driven by short-term dyadic emotional exchanges, we construct four additional control variables capturing the relative importance of immediate interactions. For the four explanatory network variables (i.e., Positive_Indegree_Source, Negative_Indegree_Source, Positive_Outdegree_Target, Negative_Outdegree_Target), we calculate the corresponding proportion of emotional interactions occurring within one day. These measures capture the extent to which recent emotional exposure is concentrated in immediate dyadic exchanges. The main results remain substantively unchanged.

Table A7 Robustness Check 3: No Heuristic to Construct the Reply Network

	(1)	(2)	(3)
Dependent Variable	Positive	Negative	Is_Positive
Specification	Marginal	Marginal	Conditional
Positive_Indegree_Source	0.152***	0.148*	0.037
	(0.054)	(0.087)	(0.037)
Negative_Indegree_Source	-0.054	-0.177**	-0.047
	(0.051)	(0.083)	(0.036)
Positive_Outdegree_Target	0.391***	0.298***	0.152***
	(0.046)	(0.069)	(0.027)
Negative_Outdegree_Target	-0.381***	-0.135*	-0.201***
	(0.044)	(0.071)	(0.029)
Network Controls			
Positive_Repetition	0.396***	0.386***	0.008
	(0.040)	(0.063)	(0.013)
Negative_Repetition	0.301***	0.441***	-0.027**
	(0.038)	(0.072)	(0.013)
Positive_Reciprocation	0.595***	0.295***	0.073***
	(0.037)	(0.054)	(0.013)
Negative_Reciprocation	0.205***	0.568***	-0.130***
	(0.033)	(0.069)	(0.012)
Positive_Outdegree_Source	0.454***	0.661***	-0.013
	(0.048)	(0.079)	(0.031)
Negative_Outdegree_Source	0.099**	0.088	0.001
	(0.047)	(0.076)	(0.032)
Positive_Indegree_Target	0.860***	0.584***	0.086***
	(0.056)	(0.090)	(0.033)
Negative_Indegree_Target	0.099*	0.282***	-0.115***
	(0.054)	(0.090)	(0.033)
Positive_Positive	-0.016	-0.231	0.101**
	(0.108)	(0.186)	(0.049)
Positive_Negative	-0.457***	-0.217	-0.083*
	(0.102)	(0.175)	(0.045)
Negative_Positive	-0.323***	-0.415**	-0.080*
	(0.097)	(0.172)	(0.044)
Negative_Negative	0.086	0.097	0.116***
	(0.095)	(0.146)	(0.041)
Other Controls	yes	yes	yes
AIC	19,688	8,433	69,624

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors are reported in parenthesis.

A11. Additional Experimental Details and Results

This section provides additional details to support the experimental results reported in the main text. Specifically, we describe the experimental procedures and stimuli, including attention and manipulation checks; present the full wording and coding of survey measures; and report supplementary mediation analyses, including complete estimation results and bootstrap confidence intervals.

A11.1. Experimental Procedures and Stimuli

Below, we describe the experimental procedures and stimuli used in the study. Participants were recruited via Prolific and screened to ensure prior experience managing a chronic condition and familiarity with online health communities. After providing informed consent, participants were

Table A8 Robustness Check 4: Controlling for Short-Term Emotional Interactions

	(1)	(2)	(3)
Dependent Variable	Positive	Negative	Is_Positive
Specification	Marginal	Marginal	Conditional
Positive_Indegree_Source	0.095**	0.135*	0.063*
	(0.043)	(0.077)	(0.035)
Negative_Indegree_Source	-0.117***	-0.149**	-0.071**
	(0.040)	(0.074)	(0.034)
Positive_Outdegree_Target	0.628***	0.420***	0.123***
	(0.037)	(0.064)	(0.026)
Negative_Outdegree_Target	-0.306***	-0.072	-0.177***
	(0.037)	(0.065)	(0.027)
Network Controls			
Positive_Repetition	0.294***	0.397***	-0.004
	(0.030)	(0.058)	(0.013)
Negative_Repetition	0.260***	0.324***	-0.022*
	(0.029)	(0.060)	(0.012)
Positive_Reciprocation	0.812***	0.701***	0.078***
	(0.032)	(0.054)	(0.012)
Negative_Reciprocation	0.334***	0.682***	-0.127***
	(0.028)	(0.059)	(0.012)
Positive_Outdegree_Source	0.591***	0.551***	0.010
	(0.040)	(0.071)	(0.031)
Negative_Outdegree_Source	0.023	0.142**	-0.019
	(0.039)	(0.071)	(0.031)
Positive_Indegree_Target	0.887***	0.609***	0.128***
	(0.045)	(0.079)	(0.032)
Negative_Indegree_Target	-0.169***	0.174**	-0.164***
	(0.043)	(0.075)	(0.031)
Friend_Friend	-0.081	0.020	0.070
	(0.100)	(0.188)	(0.047)
Friend_Enemy	-0.390***	-0.719***	-0.061
	(0.085)	(0.172)	(0.043)
Enemy_Friend	-0.283***	-0.493**	-0.074*
	(0.095)	(0.194)	(0.043)
Enemy_Enemy	0.214**	0.911***	0.122***
	(0.087)	(0.198)	(0.039)
Dyadic Intensity Ratio Controls			
Positive_Indegree_Source_1day	0.006	0.039**	-0.031***
	(0.006)	(0.017)	(0.011)
Negative_Indegree_Source_1day	0.043***	0.061***	-0.011
	(0.010)	(0.018)	(0.009)
Positive_Outdegree_Target_1day	0.067***	0.055***	0.009
	(0.010)	(0.015)	(0.009)
Negative_Outdegree_Target_1day	0.046***	0.114***	-0.010
	(0.009)	(0.022)	(0.008)
Other Controls	yes	yes	yes
AIC	28,840	10,942	77,227

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors are reported in parentheses.

randomly assigned to one of ten experimental conditions defined by emotional valence (positive, negative, neutral), content orientation (feeling-oriented vs. disease-oriented for emotionally valenced conditions), and interaction role (receiving vs. observing). Each participant completed the study in a single session and was exposed to only one condition.

At the beginning of the experiment, participants received condition-specific instructions. In the receiving conditions, participants were asked to imagine themselves as users of an online healthcare forum who had recently posted about their chronic condition and subsequently received replies from other community members. In the observing conditions, participants were instructed to imagine encountering another community member's recent posts within the community. Participants were then exposed to a fixed sequence of eight posts corresponding to their assigned condition. The posts were designed to resemble typical online health community discussions and varied systematically by emotional valence and, where applicable, content orientation. Positive and negative posts expressed either feeling-oriented content (emphasizing empathy, emotional sharing, and affective support) or disease-oriented content (emphasizing symptoms, treatments, and condition-related experiences). Neutral posts were largely informational and affectively neutral in nature and therefore did not vary by content orientation. To maintain internal validity, posts were matched across conditions on length and sentiment intensity, while differing only in emotional valence and content orientation.

All participants within a given condition viewed the same set of eight posts, presented sequentially, to ensure consistency across observations. Validation analyses confirmed that participants reliably perceived disease-oriented posts as more disease-focused than feeling-oriented posts while holding emotional valence constant. On a 7-point scale assessing content orientation (1 = completely feeling-oriented; 7 = completely disease-oriented), disease-oriented posts were rated substantially higher than feeling-oriented posts for both positive (M $\approx$ 4.73 vs. 2.22) and negative (M $\approx$ 4.71 vs. 2.54) emotional valence. At the same time, emotional valence ratings were comparable across content orientations, with positive feeling-oriented and disease-oriented posts both rated highly positive (M $\approx$ 6), and negative feeling-oriented and disease-oriented posts both rated highly negative (M $\approx$ 2). These checks indicate that the stimuli successfully operationalized the intended manipulations. In the following, we provide the representative examples of the stimuli.

Positive, Feeling-Oriented: "I totally understand where you're coming from. After months of feeling stuck, I decided to join a local support group. Everyone was so welcoming, and sharing our stories really made me feel less alone. I'm already looking forward to the next session. "

Positive, Disease-Oriented: "I totally understand where you're coming from. I recently joined a local patient group and learned evidence-based strategies for medication timing. After applying them, my symptoms improved faster than expected. I'm now looking forward to continuing the program because it's working really well. ”

Negative, Feeling-Oriented: “I've done everything. Every treatment, every therapy, every so-called ‘promising’ approach. None of it mattered. I feel like I'm throwing everything I have into a black hole, hoping for something—anything—to change. But it never does. And I don't think it ever will. ”

Negative, Disease-Oriented: “I've gone through multiple meds in the past few months, and each one stops being effective after a short period. The attacks have been lasting longer than before and aren't responding well to abortive treatments. It's reached a point where entire blocks of the week are written off because the symptoms don't ease enough to function normally. ”

Neutral: “You've mentioned putting effort into refining your treatment plan. Have you tracked any specific patterns or triggers that seem to affect your symptoms? Identifying those has been suggested as a way to adjust treatments. ”

A11.2. Measures and Variable Construction

Participants' mental resources were measured using two established scales: optimism and resilience. Optimism was measured using the Life Orientation Test–Revised (LOT-R; Scheier et al. 1994), and resilience was measured using the Brief Resilience Scale (BRS; Smith et al. 2008). Participants completed these measures prior to stimulus exposure to capture baseline mental resources and again after viewing the experimental stimuli to assess post-exposure mental resources. In the main analyses, mental resources are operationalized using post-exposure measures, consistent with the experimental design in which emotional exposure precedes mediator assessment, while baseline mental resource is used as a control variable. Following standard practice, we construct a composite mental resource index by first converting the LOT-R score—originally computed as the sum of six items—into a mean score and then averaging this value with the mean BRS score, ensuring that optimism and resilience contribute equally to the final mental resource metric. In the receiving conditions, we assess participants' likelihood of continued participation in the community and their preferred sentiment for future interactions. In the observing conditions, participants evaluated the perceived resourcefulness of the focal user whose posts they observed. Specifically, participants indicated the extent to which engaging with the focal user would represent a benefit to or a threat to their own mental resources, following prior work on resource-based social perception (Campbell et al. 2017). Participants then reported their likelihood of interacting with the focal user and, conditional on interaction, the sentiment they would choose to express in their response. Table A9 summarizes the survey questions we used. To ensure data quality, our survey included attention checks and manipulation checks. Attention checks verified that participants carefully read the posts, while manipulation checks confirmed that the sentiment of the posts (positive, negative, or neutral) were perceived as intended.

A11.3. Supplementary Mediation Analysis Results

Figure A6 shows the mean of the mental resource levels and behavioral tendencies for each receiving condition. The blue solid line represents mental resource levels, showing a decline as the emotional tone received shifts from positive to negative. This suggests that receiving negative emotions depletes mental resources, whereas positive emotions help sustain them. The green dotted line represents future reply likelihood, which also declines with more negative emotional input. This indicates that participants who receive negative emotions are less likely to engage in future interactions. The red dash-dotted line represents future emotional tendency, showing that individuals who receive negative emotions tend to express more negative emotions in subsequent interactions compared to those who receive positive emotions.

Figure A7 illustrates the effects of observing positive, neutral, and negative emotions on the perception of others and future behavioral tendency to interact with the observed individual. The green dashed line represents perceived benefit, which declines sharply as the emotional valence observed shifts from positive to negative. This suggests that individuals who express positive emotions are seen as beneficial social partners, whereas those who express negative emotions are perceived as less advantageous to engage with. The red solid line represents perceived threat, showing an increase when individuals observe negative emotional expressions. This indicates that users who frequently

Table A9 Survey Questions

Questions	Response Options
0a. (Baseline LOT-R) Please indicate the degree to which you agree or disagree with each statement based on how you generally feel about managing your health condition. E.g., In uncertain times of my health conditions, I usually expect the best. (Scheier et al. 1994)	[1] = strongly disagree [5] = strongly agree
0b. (Baseline BRS) Please indicate how well each statement describes your general ability to handle challenges or setbacks related to your health. E.g., I tend to bounce back quickly after experiencing health-related setbacks. (Smith et al. 2008)	[1] = strongly disagree [5] = strongly agree
Receiving Conditions *Prompt Summary: Imagine you are an active member of an online health forum dedicated to supporting individuals managing chronic conditions. You've created an account (User111) to engage with others, share your experiences, and gain insights from the community. Recently, you shared a couple of posts about your health journey, and other users have replied to them. Below, you will find the replies you received from other forum members.*	
1. (Manipulation check) How would you describe the emotional tone of the replies you (User111) received from others?	[1] = extremely negative [5] = extremely positive
2a. (LOT-R) After reading these replies, please indicate the degree to which you agree or disagree with each statement based on how you (User111) feel. E.g., In uncertain times of my health conditions, I usually expect the best. (Scheier et al. 1994)	[1] = strongly disagree [5] = strongly agree
2b. (BRS) After reading these replies, please indicate how well it describes your ability (as User111) to handle challenges or setbacks, particularly in managing your health. E.g., I tend to bounce back quickly after experiencing health-related setbacks. (Smith et al. 2008)	[1] = strongly disagree [5] = strongly agree
3. To what extent you (as User111) will continue interact with the forum members in the near future?	[1] = extremely unlikely [5] = extremely likely
4. How would the above replies to your posts influence the way you express emotions in this forum afterward? I tend to express emotions that are:	[1] = extremely negative [5] = extremely positive
Observing Conditions *Prompt Summary: Imagine you are an active member of an online health forum dedicated to supporting individuals managing chronic conditions. You've created an account (User111) to engage with others, share your experiences, and gain insights from the community. Recently, you have observed another user, User333, sending out the following replies to other users. Please take your time carefully reading through each reply sent by User333 and answer the questions that follow.*	
1. (Manipulation check) How would you describe the emotional tone of the replies that User333 sent to others?	[1] = extremely negative [5] = extremely positive
2. Do you think User333 is a beneficial source of optimism/resilience for you? (Campbell et al. 2017)	[1] = strongly disagree [5] = strongly agree
3. Do you think User333 is a threat to your optimism/resilience? (Campbell et al. 2017)	[1] = strongly disagree [5] = strongly agree
4. To what extent you will reply to User333 in the near future?	[1] = extremely unlikely [5] = extremely likely
5. How would User333's replies influence the way you express emotions to him/her afterward? I tend to express emotions that are:	[1] = extremely negative [5] = extremely positive

express negative emotions may be perceived as emotionally depleting or even harmful to others' mental resources. The blue dotted line represents future reply likelihood, which declines as more negative emotions are observed. This suggests that people are less likely to engage with individuals who consistently express negative emotions. Lastly, the orange dash-dotted line represents future emotional tendency, which shows that people who observe positive (negative) emotions tend to respond with more (less) positive sentiment.

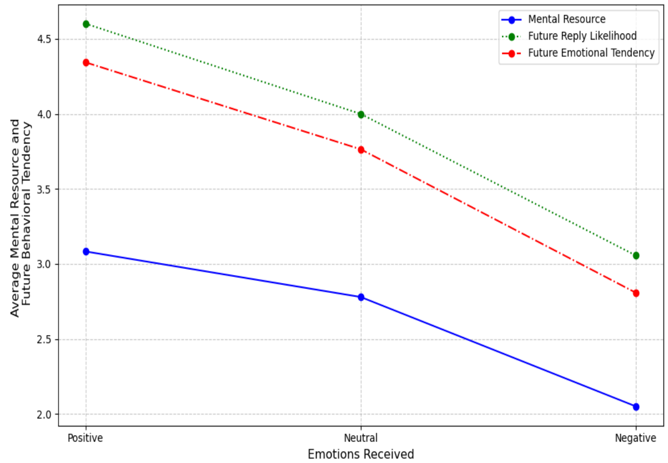

Figure A6 **Mean Mental Resource Levels and Behavioral Tendencies by Receiving Conditions**

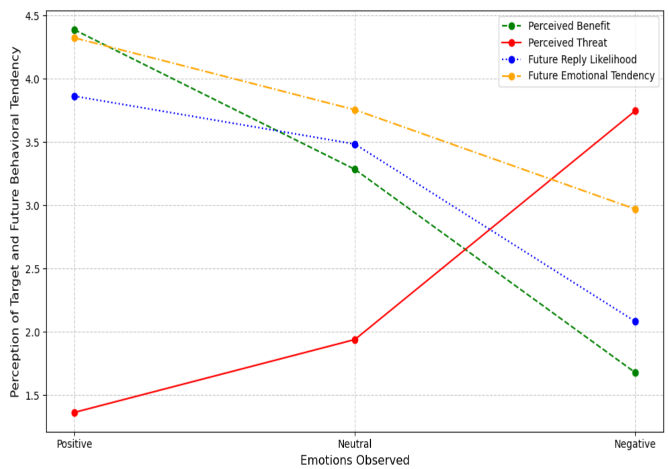

Figure A7 **Perception of Target and Behavioral Tendencies by Observing Conditions**

A11.3.1. Overall Mediation Results. In the following, we report detailed estimation results for the regression-based mediation analyses summarized in the main text. For each comparison between emotional valence conditions and the neutral baseline, we report indirect effects (ab) and their bootstrap confidence intervals, and the proportion of the total effect mediated by mental resources. All mediation effects are estimated using nonparametric bootstrap procedures with 2,000 resamples.

Receiving Conditions. In the receiving-positive versus neutral comparison, emotional valence has a significant positive total effect on both engagement likelihood and emotional tendency. Mental resources partially mediate these effects. For engagement likelihood, the indirect effect is positive and statistically significant (ab = 0.109, 95% CI [0.043, 0.197]), accounting for approximately 18.5% of the total effect. For emotional tendency, the indirect effect is similarly significant (ab = 0.104, 95% CI [0.045, 0.178]), with mental resources accounting for approximately 18.6% of the total effect. In the receiving-negative versus neutral comparison, emotional valence exerts large negative total effects on both outcomes. Mental resources again play a substantial mediating role. The indirect effect accounts for approximately 34.2% of the total effect on engagement likelihood (ab = -0.326, 95% CI [-0.528, -0.135]) and 45.8% of the total effect on emotional tendency (ab = -0.474, 95% CI [-0.640, -0.321]).

Observing Conditions. In the observing-positive versus neutral comparison, emotional valence has a positive total effect on engagement likelihood and emotional tendency. These effects are strongly mediated by perceived benefits to mental resources. For engagement likelihood, the indirect effect is large and statistically significant (ab = 0.845, 95% CI [0.651, 1.062]), exceeding the magnitude of the total effect and indicating a suppression pattern. For emotional tendency, the indirect effect is also significant (ab = 0.353, 95% CI [0.246, 0.473]), accounting for approximately 67.3% of the total effect. In the observing-negative versus neutral comparison, emotional valence has large negative effects on both outcomes. These effects are partially mediated by perceived threats to mental resources. The indirect pathway accounts for approximately 51.7% of the total effect on engagement likelihood (ab = -0.721, 95% CI [-1.016, -0.452]) and 49.4% of the total effect on emotional tendency (ab = -0.397, 95% CI [-0.593, -0.209]).

Overall, the appendix results confirm that mental resources consistently mediate the relationship between emotional valence and engagement-related outcomes, with mediation strength varying by interaction role and outcome type. Regression outputs and bootstrap confidence intervals are reported in Tables A10–A13.

A11.3.2. Pre–Post Analysis of Mental Resources in Receiving vs. Observing Conditions To further clarify the psychological mechanisms underlying the mediation results, we conduct an additional pre–post analysis of mental resources to distinguish whether emotional influence

Table A10 Bootstrap Mediation Results (Receiving Conditions): Reply Likelihood

Condition (vs. Neutral)	Total Effect c	Direct Effect c'	Indirect Effect ab	95% Bootstrap CI (ab)	Prop. Mediated	N
Positive	0.589	0.480	0.109	[0.043, 0.197]	0.185	285
Negative	-0.954	-0.628	-0.326	[-0.528, -0.135]	0.342	282

Table A11 Bootstrap Mediation Results (Receiving Conditions): Emotional Tendency

Condition (vs. Neutral)	Total Effect c	Direct Effect c'	Indirect Effect ab	95% Bootstrap CI (ab)	Prop. Mediated	N
Positive	0.561	0.456	0.104	[0.045, 0.178]	0.186	285
Negative	-1.034	-0.561	-0.474	[-0.640, -0.321]	0.458	282

Table A12 Bootstrap Mediation Results (Observing Conditions): Reply Likelihood

Condition (vs. Neutral)	Total Effect c	Direct Effect c'	Indirect Effect ab	95% Bootstrap CI (ab)	Prop. Mediated	N
Positive	0.351	-0.494	0.845	[0.651, 1.062]	2.409[a]	257
Negative	-1.396	-0.675	-0.721	[-1.016, -0.452]	0.517	254

Notes. The mediator in observing-positive conditions is perceived benefit of the focal user.

[a] For positive vs. neutral, the direct and indirect effects operate in opposite directions (suppression/competitive mediation).

Table A13 Bootstrap Mediation Results (Observing Conditions): Emotional Tendency

Condition (vs. Neutral)	Total Effect c	Direct Effect c'	Indirect Effect ab	95% Bootstrap CI (ab)	Prop. Mediated	N
Positive	0.524	0.172	0.353	[0.246, 0.473]	0.673	257
Negative	-0.805	-0.407	-0.397	[-0.593, -0.209]	0.494	254

Notes. The mediator in observing-negative conditions is perceived threat of the focal user.

operates through changes in individuals' own mental resources or through perceptions of others' mental resources across interaction roles. Specifically, we directly measure participants' mental resources (LOT-R and BRS) both before and after exposure to emotional messages, separately for the receiving and observing conditions.

In the receiving conditions, paired-sample tests reveal significant within-individual changes in mental resources following emotional exposure. Receiving positive replies significantly increases mental resources (pre-exposure $M = 2.86$; post-exposure $M = 3.14$; $t(49) = -2.65$, $p = 0.011$), whereas receiving negative replies significantly reduces mental resources (pre-exposure $M = 3.02$; post-exposure $M = 2.23$; $t(49) = 5.40$, $p < 0.001$). In contrast, in the observing conditions, neither observing positive replies (pre-exposure $M = 3.07$; post-exposure $M = 3.13$; $t(51) = -1.25$, $p = 0.217$) nor observing negative replies (pre-exposure $M = 2.93$; post-exposure $M = 2.91$; $t(49) = 0.44$, $p = 0.664$) produces significant within-individual changes in mental resources.

These results indicate that emotional influence in the observing context does not operate through changes in individuals' own mental resources, but instead through resource-based social evaluations of others, that is, perceptions of whether another user represents a benefit or a threat to one's mental resources. This interpretation is consistent with the mediation analyses reported above, which show that observing emotional expressions significantly shapes perceived resourcefulness of others and downstream interaction choices. Collectively, the pre–post analysis provides clear empirical support for the proposed duality of ERC and EFE.

A11.3.3. Mediated Effects Across Content Orientations This subsection reports detailed results from bootstrap mediation analyses comparing indirect effects across feeling-oriented and disease-oriented emotional expressions. Emotional valence conditions (positive and negative) are decomposed into disease-oriented and feeling-oriented arms and compared against a neutral baseline. Indirect effects are estimated using nonparametric bootstrapping with 2,000 resamples, and differences in indirect effects across arms are evaluated using bootstrap confidence intervals.

Receiving Conditions. In the receiving-positive condition, both disease-oriented and feeling-oriented content exhibit statistically significant indirect effects on engagement likelihood and emotional tendency through mental resources. Specifically, relative to the neutral baseline, disease-oriented content yields an indirect effect of 0.116 on engagement likelihood (95% CI [0.024, 0.239]), while feeling-oriented content yields an indirect effect of 0.104 (95% CI [0.039, 0.195]). The difference between these indirect effects is small and not statistically significant, indicating comparable mediation strength across content orientations. A similar pattern emerges for emotional tendency, with no significant difference in indirect effects between disease-oriented and feeling-oriented positive expressions. In the receiving-negative condition, both content orientations again produce significant negative indirect effects through mental resources. Feeling-oriented content consistently exhibits larger indirect effects than disease-oriented content for both engagement likelihood and emotional tendency. While the difference in indirect effects is not significant at the 95% level, it is marginally significant at the 90% level, suggesting marginal evidence that feeling-oriented framing amplifies the indirect effect in the receiving context.

Observing Conditions. In the observing-positive condition, content orientation plays a substantial role in shaping mediation strength. Relative to the neutral baseline, disease-oriented positive expressions generate a significant indirect effect on reply likelihood (IE = 0.626, 95% CI [0.397, 0.868]), whereas feeling-oriented expressions generate a markedly larger indirect effect (IE = 1.058, 95% CI [0.816, 1.299]). The difference between these indirect effects is statistically significant (ΔIE = 0.432, 95% CI [0.212, 0.688]). Parallel patterns emerge for emotional tendency, with feeling-oriented content producing significantly stronger mediated effects than disease-oriented content. In the observing-negative condition, both disease-oriented and feeling-oriented expressions yield significant negative indirect effects through perceived threats to mental resources. Feeling-oriented negative expressions again produce significantly larger indirect effects than disease-oriented expressions for both engagement likelihood (ΔIE = -0.285, 95% CI [-0.490, -0.106]) and emotional tendency (ΔIE = -0.150, 95% CI [-0.282, -0.049]).

Overall, these results demonstrate that content orientation significantly moderates resource-based mediation in observing contexts but plays a more limited role in receiving contexts. Full indirect effect estimates, confidence intervals, and contrasts are reported in Tables A14–A17.

Table A14 Mediation Results by Content Orientation (Receiving Conditions): Reply Likelihood

Condition (vs. Neutral)	Total Effect c	Direct Effect c'	Indirect Effect ab	95% CI (ab)	90% CI (ab)	N
Positive, Disease-Oriented	0.677	0.561	0.116	[0.024, 0.239]	[0.035, 0.217]	285
Positive, Feeling-Oriented	0.533	0.429	0.104	[0.039, 0.195]	[0.046, 0.177]	285
Difference (Feeling – Disease)	–	–	-0.012	[-0.109, 0.081]	[-0.092, 0.068]	–
Negative, Disease-Oriented	-0.949	-0.689	-0.261	[-0.457, -0.099]	[-0.423, -0.118]	282
Negative, Feeling-Oriented	-0.958	-0.577	-0.381	[-0.621, -0.155]	[-0.577, -0.188]	282
Difference (Feeling – Disease)	–	–	-0.121	[-0.283, 0.010]	[-0.252, -0.011]	–

Notes. Confidence intervals for differences are obtained by bootstrapping the contrast in indirect effects.

Table A15 Mediation Results by Content Orientation (Receiving Conditions): Emotional Tendency

Condition (vs. Neutral)	Total Effect c	Direct Effect c'	Indirect Effect ab	95% CI (ab)	90% CI (ab)	N
Positive, Disease-Oriented	0.541	0.430	0.111	[0.029, 0.213]	[0.040, 0.192]	285
Positive, Feeling-Oriented	0.573	0.474	0.100	[0.038, 0.183]	[0.047, 0.165]	285
Difference (Feeling – Disease)	–	–	-0.011	[-0.103, 0.081]	[-0.087, 0.064]	–
Negative, Disease-Oriented	-1.115	-0.731	-0.384	[-0.572, -0.213]	[-0.544, -0.238]	282
Negative, Feeling-Oriented	-0.980	-0.418	-0.562	[-0.755, -0.381]	[-0.718, -0.407]	282
Difference (Feeling – Disease)	–	–	-0.178	[-0.382, 0.008]	[-0.342, -0.021]	–

Notes. Confidence intervals for differences are obtained by bootstrapping the contrast in indirect effects.

Table A16 Mediation Results by Content Orientation (Observing Conditions): Reply Likelihood

Condition (vs. Neutral)	Total Effect c	Direct Effect c'	Indirect Effect ab	95% CI (ab)	90% CI (ab)	N
Positive, Disease-Oriented	0.085	-0.541	0.626	[0.397, 0.868]	[0.429, 0.828]	257
Positive, Feeling-Oriented	0.628	-0.430	1.058	[0.816, 1.299]	[0.858, 1.260]	257
Difference (Feeling – Disease)	–	–	0.432	[0.212, 0.688]	[0.246, 0.643]	–
Negative, Disease-Oriented	-1.219	-0.646	-0.573	[-0.857, -0.336]	[-0.813, -0.369]	254
Negative, Feeling-Oriented	-1.578	-0.721	-0.858	[-1.191, -0.547]	[-1.124, -0.601]	254
Difference (Feeling – Disease)	–	–	-0.285	[-0.490, -0.106]	[-0.462, -0.139]	–

Notes. Indirect effects reflect mediation through perceived benefits to one's mental resources. Confidence intervals for differences are obtained by bootstrapping the contrast in indirect effects.

Table A17 Mediation Results by Content Orientation (Observing Conditions): Emotional Tendency

Condition (vs. Neutral)	Total Effect c	Direct Effect c'	Indirect Effect ab	95% CI (ab)	90% CI (ab)	N
Positive, Disease-Oriented	0.413	0.152	0.261	[0.149, 0.381]	[0.166, 0.364]	257
Positive, Feeling-Oriented	0.640	0.199	0.442	[0.315, 0.578]	[0.332, 0.558]	257
Difference (Feeling – Disease)	–	–	0.180	[0.088, 0.303]	[0.100, 0.275]	–
Negative, Disease-Oriented	-0.631	-0.329	-0.301	[-0.480, -0.135]	[-0.455, -0.164]	254
Negative, Feeling-Oriented	-0.984	-0.532	-0.451	[-0.702, -0.214]	[-0.655, -0.254]	254
Difference (Feeling – Disease)	–	–	-0.150	[-0.282, -0.049]	[-0.259, -0.061]	–

Notes. Indirect effects reflect mediation through perceived threat to one's mental resources. Confidence intervals for differences are obtained by bootstrapping the contrast in indirect effects.

References

Campbell EM, Liao H, Chuang A, Zhou J, Dong Y (2017) Hot shots and cool reception? an expanded view of social consequences for high performers. *Journal of Applied Psychology* 102(5):845.

Schecter A, Pilny A, Leung A, Poole MS, Contractor N (2018) Step by step: Capturing the dynamics of work team process through relational event sequences. *Journal of Organizational Behavior* 39(9):1163–1181.

Scheier MF, Carver CS, Bridges MW (1994) Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): a reevaluation of the life orientation test. *Journal of personality and social psychology* 67(6):1063.

Smith BW, Dalen J, Wiggins K, Tooley E, Christopher P, Bernard J (2008) The brief resilience scale: assessing the ability to bounce back. *International journal of behavioral medicine* 15:194–200.