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Online posting effects: Unveiling the non-linear journeys of users in depression communities on Reddit

Virginia Morini [a,b,1], Salvatore Citraro [b,1], Elena Sajno [a,c,2], Maria Sansoni [d,2], Giuseppe Riva [e], Massimo Stella [f,3,*], Giulio Rossetti [b,3]

[a] Department of Computer Science, University of Pisa, Pisa, Italy
[b] Institute of Information Science and Technologies "A. Faedo" (ISTI), National Research Council (CNR), Pisa, Italy
[c] Humane Technology Lab, Catholic University of the Sacred Heart, Milan, Italy
[d] Department of Psychology, Catholic University of the Sacred Heart, Milan, Italy
[e] Applied Technology for Neuro-Psychology Lab, IRCCS Istituto Auxologico Italiano, Milan, Italy
[f] CogNosco Lab, Department of Psychology and Cognitive Science, University of Trento, Trento, Italy

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ABSTRACT

Social media platforms have become pivotal as self-help forums, enabling individuals to share personal experiences and seek support. However, on topics as sensitive as depression, what are the consequences of online self-disclosure? Here, we delve into the dynamics of mental health discourse on various Reddit boards focused on depression. To this aim, we introduce a data-informed framework reconstructing online dynamics from 303k users interacting over two years. Through user-generated content, we identify 4 distinct clusters representing different psychological states. Our analysis unveils online posting effects: a user can transition to another psychological state after online exposure to peers' emotional/semantic content. As described by conditional Markov chains and different levels of social exposure, users' transitions reveal navigation through both positive and negative phases in a spiral rather than a linear progression. Interpreted in light of psychological literature, related particularly to the Patient Health Engagement (PHE) model, our findings can provide evidence that the type and layout of online social interactions have an impact on users' "journeys" when posting about depression.

1. Introduction

Approximately one out of 26 people suffered from depressive symptoms in their lives (GBD, 2019). Depression can deeply affect how people feel, think, act and communicate (Clark, Beck, Alford, Bieling, & Segal, 2000). As a condition of negative affect, depression can correspond to feelings of hopelessness, devaluation of life, anhedonia and self-deprecation, among others (Lovibond & Lovibond, 1995). Traditionally, support for depression primarily involved direct, in-person interactions, where the physical presence of a therapist or support group could provide tangible, empathetic assistance (Clark et al., 2000; Naslund, Aschbrenner, Marsch, & Bartels, 2016). In the last few decades, the World Wide Web has shifted much of peer support to online social platforms (OSPs) (Escobar-Viera, Shensa, Bowman, Sidani, Knight, James, & Primack, 2018). These digital spaces provide a venue where individuals can anonymously share their experiences and seek support, thus expanding access to assistance beyond conventional therapeutic environments (De Duro, Improta, & Stella, 2024).

The importance of seeking social support is well documented, as these interactions can play a critical role in the recovery process by building a support network, validating feelings, and sharing coping strategies (Garssen, Visser, & Pool, 2021; Lazarus & Folkman, 1984). Indeed, online self-help groups offer the advantage of reaching potentially larger audiences and allowing for interaction without time and space constraints. This translates into immediate help and a constant availability that traditional settings cannot match (Joseph, Citraro, Morini, Rossetti, & Stella, 2023; Naslund et al., 2016). While this online shift has made seeking help for depression more accessible, it has also introduced complexities relative to how support can be provided and received, thus raising an important question: *Do online discussions benefit people debating depression?*

* Corresponding author.
E-mail address: giulio.rossetti@isti.cnr.it (G. Rossetti).
[1] These authors provided equal contributions.
[2] These authors provided equal contributions.
[3] These authors provided equal contributions.

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This research question can be explored at multiple levels, some more challenging than others. One way could be to quantify people's "benefit" in terms of understanding how online social interactions influence users' perceived depression symptoms over time. However, exploring this aspect at the individual level requires external validation coming from mental health professionals. The latter would have to follow online users' patient journeys with depression, i.e. the fluctuations of mood and well-being relative to coping or dealing with depressive symptoms (Graffigna, Barello, & Riva, 2013; Lovibond & Lovibond, 1995). Whereas online data on OSPs is relatively easily available, e.g., Reddit counts thousands of posts in depression-related communities (Joseph et al., 2023), external validation from experts is scarcely available, mainly because of anonymity, confidentiality, and lack of diagnosis (Ma, Hancock, & Naaman, 2016). This methodological challenge creates a significant gap in understanding how online discussions affect users' mental well-being, particularly given the massive scale of online mental health communities (Pantic, 2014; Tang, Yu, & Yao, 2021). To address this gap, researchers have disregarded individual-based questionnaires and relied on artificial intelligence (AI) methods to map digital traces (e.g., users' posts or likes) (Stella, 2022) in mental well-being dimensions of distress. Most of these studies (Escobar-Viera et al., 2018; Fatima, Abbasi, Khan, Al-Saeed, Ahmad, & Mumtaz, 2019; Fatima, Li, Hills, & Stella, 2021) usually focus on predicting distress levels within individual posts, one by one, crucially neglecting social or time-wise interactions among users.

We argue that users in OSPs cannot be reduced to sequences of likes or posts but are rather complex systems entwining cognitive content, emotional perspectives, and mental well-being dimensions. To tackle all these directions at once, we tap into theoretical frameworks spanning cognitive data science (Stella, 2022), clinical psychology (Clark et al., 2000; Graffigna et al., 2013), psycholinguistics (Tausczik & Pennebaker, 2010), natural language processing (Joseph et al., 2023) and social network analysis (Rossetti & Cazabet, 2018). Focusing on the Reddit platform, here we investigate the above complexities by harnessing whether online debates on depression can correspond to alterations, either positive or negative, in users' expressed well-being over time.

To this aim, in the following we briefly discuss key aspects of OSPs and their role in mental health self-disclosure and psychological content engagement.

Self-disclosure on OSPs like Reddit

In psychotherapy, disclosing personal experiences for seeking mental health support is a well-established practice (Clark et al., 2000; Holahan, Moos, Holahan, Brennan, & Schutte, 2005). Whereas therapy traditionally occurs between the therapist and the client, nowadays, OSPs have quickly become self-help communities where users share personal information with peers facing similar challenges (Huffaker, 2010; Pantic, 2014; Tang et al., 2021). These exchanges often involve conversations or discussions among more than two users at a time, all protected by the anonymity OSPs offer (Naslund et al., 2016). Recent literature discusses how anonymity, due to the online disinhibition effect (Ma et al., 2016), can make it easier to disclose personal information with strangers rather than with personal acquaintances.

Among OSPs, Reddit is a social platform where users post content to forums called *subreddits*, each dedicated to specific topics or interests. Also Reddit allows almost complete anonymity – unless users choose otherwise – enabling discussions about sensitive issues and disclosures of personal experiences (Ma et al., 2016). These exchanges are often moderated in ways that every user could be comfortable enough to share their own thoughts in a safe environment without toxic social interactions (Almerekhi, Jansen, & Kwak, 2020). Furthermore, users can either provide or seek support, thus impersonating more than one role in the same community (e.g., caregiver or help-seeker) (Balsamo, Bajardi, Morales, Monti, & Schifanella, 2023). Beyond communicative roles and their relative intentions, e.g., seeking support or providing trust, users on Reddit can engage in different threads over time and potentially undergo some inner changes. In other words, users can change or evolve in their communicative intentions over time after exposure to online content or personal happenings in their offline lives. Despite the latter events occurring outside the online world, users might still report events in their lives within Reddit boards, ultimately using subreddits as personal diaries (Abramski, Ciringione, Rossetti, & Stella, 2024).

The psychology of content engagement

Using Reddit communities as personal diaries crucially enriches the online environment with a wide variety of real-world and personal events. In turn, this richness increases the chances that online content might appeal, trigger or resonate with other users, potentially going through similar or disparate events (Almerekhi et al., 2020). Ultimately, people might react in different ways after being exposed to such rich digital content via online social interactions. Accordingly, past works have found that even reading online content can be a powerful experience for someone's affect and cognition (Goldenberg & Gross, 2020; Joseph et al., 2023; Kramer, Guillory, & Hancock, 2014). This phenomenon, known as *emotional contagion*, refers to the act of any two individuals exchanging knowledge and converging towards the same emotional state (Hatfield, Cacioppo, & Rapson, 1993). Emotional contagion was found to occur also in the absence of face-to-face interactions: Even reading online posts (Kramer et al., 2014) can alter the emotional states of people and the effect lasts for hours (Ferrara & Yang, 2015). As a consequence, engaging with different types of content can elicit different reactions in users participating in the same discussion thread.

How do users express their own reactions? On Reddit, users can express their thoughts mostly via posts, endorsements, replies, and- re-sharings, leaving digital traces that can thus be considered as proxies into users' expressed psychological state at the moment of writing (Fatima et al., 2019; Huffaker, 2010; Joseph et al., 2023). It is important to underline that digital traces cannot fully reconstruct the psychology of an online user. Instead, these traces represent proxies that can partially reconstruct what users are talking about and how they emotionally perceive something (Stella, 2022). These two elements map semantic- and emotional content of users' psychology and could potentially be used to identify clusters of users sharing similar psychological features. This passage is supported by rich psychological literature establishing a link between people's language and their psychological features.

In general, the Deep Lexical Hypothesis (Uher, 2013) posits that psychological constructs and traits can percolate through one's psychology up to alter people's language (Cutler & Condon, 2022). Focusing on depression, several studies have identified that individuals with higher depressive symptoms exhibit the following features in their language: (i) absolutist thinking (Al-Mosaiwi & Johnstone, 2018) (e.g., a black-and-white vision of the world), (ii) self-focused language (Al-Mosaiwi & Johnstone, 2018; Rude, Gortner, & Pennebaker, 2004) (e.g., mentioning the self disproportionately), (iii) negative emotions (Stephan et al., 2013; Tausczik & Pennebaker, 2010) (e.g., overabundance of anger and fear) and (iv) a low sense of dominance and agency (Stephan et al., 2013) (e.g. an inability for someone to feel in control of their life events). Hence, these features can help in discerning different levels or categories of users debating and affected by depression to different extents.

These features of posts and/or comments, merged with their underlying social interactions, provide a complex yet rich snapshot of online social debate about depression. In other words, we argue that next-generation computational social science studies should go beyond modeling social networks as "skeletons" of who-answers-to-whom and rather embrace the psychological, cognitive, and time-evolving nature of online human interactions, especially within online supportive communities.

Research challenges and study aims

Following this reasoning, this study focus on understanding how online social interactions taking place on Reddit affect individuals discussing depression. While prior research has explored depression detection on social media (Escobar-Viera et al., 2018; Fatima et al., 2019; Kamarudin, Beigi, & Liu, 2021), the psychological impact of these interactions remains poorly understood. Here, we propose a novel framework that combines psycholinguistic analysis with social network dynamics to investigate how users' psychological states evolve through online interactions.

Unlike previous studies, we examine how users' language and social connections jointly reflect their psychological journey. While acknowledging that someone's language may not overlap entirely with their mental state (Gentzkow, Kelly, & Taddy, 2019), our approach combines psycholinguistic features extracted from users' content, social interaction patterns captured through network analysis, and temporal dynamics modeled via conditional Markov chains.

This methodological framework addresses our main research question:

RQ1. *How do online interactions within support communities impact individuals' psychological states?*

To fully investigate this general question, we further explore two specific aspects:
RQ1.1. Do individuals' psychological states form distinct patterns that could align with established psychological models?
RQ1.2. Do users progress linearly through these states or follow more complex patterns?

From our two-year analysis of 303K Reddit users in depression-related communities, we identified four data-driven psychological states. Interestingly, these states show notable parallels with established psychological frameworks, particularly the Patient Health Engagement (PHE) model (Graffigna et al., 2013). This model describes mental health management through phases of emotional overwhelm (*blackout*), initial awareness (*arousal*), emerging engagement (*adesion*), and structured management (*eudaimonic project*) – a progression that offers valuable context for interpreting our findings, as we will discuss. Subsequently, we quantitatively reconstruct users' "journeys" through these states, introducing the concept of "posting effects" – the likelihood of transitioning between psychological states after specific types of social exposure.

Through this novel methodological lens, we find that online interactions can both improve and potentially worsen users' expressed mental well-being, challenging linear assumptions about recovery trajectories.

Method

Our study leverages a longitudinal Reddit[4] user interactions dataset. We chose Reddit as our data source for several key reasons: (i) its community-focused structure through topic-specific subreddits is widely used for mental health support-seeking, enabling targeted analysis of depression-related discussions (Proferes, Jones, Gilbert, Fiesler, & Zimmer, 2021), (ii) the platform's anonymity facilitates more open self-disclosure about mental health experiences, and (iii) its threaded discussion format allows for systematic tracking of user interactions and conversation dynamics. Given our focus on depression and following previous research (Escobar-Viera et al., 2018; Fatima et al., 2019; Kamarudin et al., 2021; Sampath & Durairaj, 2022), we selected six popular subreddits related to depression in general, treatments, and support seeking (see Table 1 for details about subscribers and activity metrics). We collected two years of data (May 1, 2018, to May 1, 2020) from these communities using the Pushshift API (Baumgartner, Zannettou, Keegan, Squire, & Blackburn, 2020), resulting in 378,483 posts and 1,475,044 comments from 303,016 unique users.[5] To ensure data quality, we implemented several cleaning steps: filtering for English-language content, removing duplicated posts/comments, empty content, and deleted accounts, and excluding content from moderators and known Reddit bots.[6] Since our focus is on user interactions, we retained only users who engaged with at least one other user. For each post and comment, we preserved essential metadata including pseudonymized author identifiers, content text, timestamps, and thread structure information. Additional details about the data collection steps are available in *SI*, Section 1.

Table 1
Dataset Description: For each considered subreddit: number of subscribers, the total number of posts and comments extracted, and the total number of users.

Subreddit	# subscribers	# posts	# comments	# users
r/depression	928,705	378,483	1,475,044	303,016
r/depressionregimens	43,832			
r/depression_help	81,971			
r/EOOD	89,686			
r/GFD	11,807			
r/sad	133,154			

In the following, we describe our analytical pipeline, focusing on its main components, namely: (i) the definition of the User Generated Contents (UGC) features used to characterize the psychological dimensions of the selected population; (ii) the identification of users' psychological states; (iii) the measuring and validation of engagement and social exposure effects on online users' journeys.

Stage 1: Mapping UGCs Psycholinguistic dimensions. We extracted a set of features from users' posts/comments along 5 psychological and linguistic dimensions:

i. *Plutchik's Primary Emotions* provides information about words' expressive level among eight basic emotions, according to the well-established Plutchik's psychoevolutionary theory of primary emotions (Plutchik, 1980); in detail, we use the emotional ratings of the NRC Lexicon[7] (Mohammad & Turney, 2013);
ii. *PAD Emotional Dimensions* measures the level of valence/pleasure, arousal, and dominance associated with users' contents, which indicates, respectively, the level of pleasantness, stimulation, and control experienced by users based on the Mehrabian and Rusell PAD model (Mehrabian & Russell, 1974); in detail, we use the NRC VAD Lexicon (Mohammad, 2018);
iii. *Sentiment* unveils whether the underlying emotional tone of users' texts appears to be positive/negative; in detail, we leverage the VADER Lexicon[8] (Hutto & Gilbert, 2014);
iv. *Taboo Rate* captures the frequency of taboo or offensive words within a given text (Reilly et al., 2020);
v. *Subjectivity* refers to the level of opinions or personal feelings expressed in users' texts, as opposed to objective facts; in detail, we rely on the TextBlob library.[9]

We assessed the significance and non-redundancy of extracted features via statistical analysis (see *SI*, Section 2).

To generate monthly scores for each user, we averaged the values of these indicators based on the content they shared. Additional details on feature extraction and preprocessing can be found in *SI*, Section 2.

[4] https://reddit.com/

[5] The anonymized data are made available in a dedicated GitHub Repository.
[6] https://botrank.pastimes.eu/
[7] https://github.com/metalcorebear/NRCLex
[8] https://github.com/cjhutto/vaderSentiment
[9] https://textblob.readthedocs.io/en/dev/

Step 2: Identifying Users' Psychological States and Discussed Topics. We used the extracted indicators to identify groups of similar users through unsupervised clustering. Each user is thus represented as a vector of feature values proxying the user's psychological state during a given month. We leverage the K-Means (MacQueen, 1967) to identify four psychological clusters based on the retrieved psycholinguistic features. The parameter value choice, $k = 4$, is driven by the elbow method, a well-known method used to estimate the best number of clusters present in a dataset. Technical details of K-Means can be found in *SI*, Section 2.

Regarding clusters' content analysis, we investigate all texts produced by users belonging to a cluster via topic modeling, i.e., an unsupervised learning method to automatically cluster groups of words that best characterize a set of documents. In detail, we rely on BERTopic (Devlin, Chang, Lee, & Toutanova, 2018) (via Python implementation[10]) to extract ten meaningful topics from each psycholinguistic cluster (see Fig. 1(a–d) of *SI*). Technical details of K-Means, and BERTopic algorithms can be found in *SI*, Section 2.

Stage 3: Measuring Social Exposure. To measure the effects of social exposure on online users' journeys, we filtered our dataset. We kept only those users (along with their interactions temporally aggregated at the monthly level) having participated in depression-related discussions for at least two consecutive months. After such a filter, the initial population was reduced by 50% (≃150.000 active users).

Leveraging such sub-population we defined different levels of social exposure and relate them to the likelihood of cluster change. Fixed a month t, a generic user u and a conditioning cluster C, we measure social exposure as a result of different levels of interactions:

- *Single Interaction*: during t, u interacted with at least a user v of cluster C - where being in contact means that u and v directly reply each other in at least a discussion thread;
- *Single Homogeneous Context*: during t, u participated at least a *discussion context* Γ whose majority of users belong to cluster C - where Γ identifies a nested sub-thread (e.g., all messages appearing at the same level in the discussion tree of a given thread). Therefore, Γ describes a set of users that, even non-replying directly to each other, participate in the same discussion.
- *Majority of Interactions*: during t, u interacted prevalently with users belonging to C;
- *Majority of Homogeneous Contexts*: during t, u participated prevalently in contexts where most users belong to cluster C.

For every exposure level, we compute the transition probability for a user to move from cluster C_i at a generic time t to cluster C_j at time $t+1$.

Levels of social exposure are modeled on the network of interactions between users. To this aim, we leverage notions from graph theory, either pairwise graphs for the *Single Interaction* and the *Majority of Interactions* models (Newman, 2018), or hypergraphs for the *Single Homogeneous Context* and the *Majority of Homogeneous Contexts* ones (Battiston et al., 2020). Direct replies between users were represented as pairwise edges between two graph nodes, whereas discussion contexts – i.e., the sub-threads – were represented using hyperedges, namely sets of nodes, of a hypergraph. On the one hand, two interacting users, i.e., replying to the same post, are linked through pairwise edges. On the other hand, hypergraphs expand on the traditional graph structure by allowing for higher-order interactions between more than two nodes (Battiston et al., 2020). Users that rely on the same level of discussion jointly form a hyperedge. Detailed references to the formal definitions and modeling choices used to capture pairwise and higher-order user interactions are reported in the SI, Section 3.

We use mathematical modeling to explore whether the above social interactions affect how individuals move across clusters over time. Specifically, we measure Constrained Transition Patterns (CTPs) as the conditional probability of observing individuals' transition from one cluster to another when users are exposed, to different degrees, to the content originating from a target cluster. Consequently, we obtain a matrix of Markov transition probabilities for every level of social exposure and constraining clusters. Note that with *constraining cluster*, we intend the cluster upon which we are conditioning.

We used two null models to statistically test the significance of those transitions. In doing so, we account for the following confounders:

i. the effect of the overall distribution of cluster labels - by destroying original users' cluster memberships;
ii. the effect of time - by destroying the temporal dependency of connectivity between users.

Regarding the former confounder, clusters' labels of all users were randomly shuffled several times, complying with the original distribution. Regarding the latter, monthly graph/hypergraph snapshots were randomly shuffled by keeping the original topologies. Then, for both models, the expected probabilities to shift between clusters were compared to the probabilities computed on the real data. Only statistically significant transitions ($p < 0.01$) were kept in the analysis. Refer to the SI, Section 3, for a more formal description of the null models and the results obtained by testing each null model independently.

Results

Our data-informed approach highlights users' transition patterns across online interactions: Users can embark on several possible journeys, transitioning across healing or turbulent paths. In the following, we report the main results provided by our analysis, focusing on (i) the description of the identified users' clusters (i.e., psychological states characterizing groups of users), (ii) the effects of social exposure as described by the statistically validated transition probabilities computed from observed online users' journeys.

1.1. Users' clusters as psychological states

We characterize every cluster in terms of (i) average features, i.e., K-Means cluster centroids as shown in Fig. 1, and (ii) cluster content via topic detection using BERTopic, see *SI* Fig. 1(a–d).

Cluster 1: High Distress State. As shown in Fig. 1(A), Cluster 1 (C1) displays a highly negative emotional profile, with prominent levels of sadness, fear and disgust and an absence of joy or trust. C1 also has higher arousal but lower dominance and valence compared to other clusters (Fig. 1(B)), indicating alarm and anxiety (Mohammad & Turney, 2013; Russell, 1980) with lower self-agency (Mohammad, 2018). C1 posts also have the most negative VADER sentiment, a higher subjectivity (Fig. 1(C,D)) and many taboo words, indicating the presence of offensive and egocentric language (Fig. 1(E)).

Topics in C1 (Fig. 1(a) of *SI*) include *Education/Work*, *Relationship*, *Need Support*, *Sleep Habits*, *Appearance*, *Meds/Doctor*, *Family*, *Suicide*, and *Self-Harm*. The presence of topics around self-harming behaviors and suicidal thoughts among online users discussing depression mirrors offline expectations from the relevant clinical literature (Clark et al., 2000). Despite the negative profile, users seek support from others, enhancing emotional well-being (Keles, McCrae, & Grealish, 2020). The negative and positive topics (Fig. 1(a) of *SI*), and overall negative profile (Fig. 1(A)) suggest ambivalence in C1 users' communicative intentions.

Cluster 2: Positive Resilient State. In contrast to the highly negative emotional profile and distressed expressions of Custer 1, Cluster 2 (C2) demonstrates markedly different characteristics, suggesting a more positive psychological state. Indeed, as shown in Fig. 1(A), C2 has higher

[10] https://github.com/MaartenGr/BERTopic

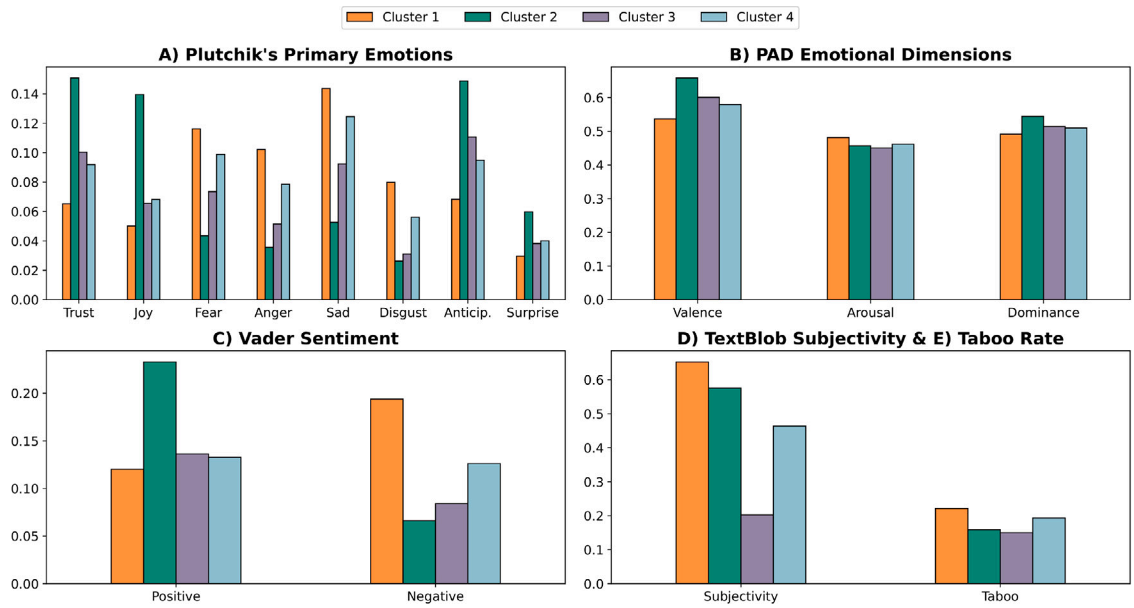

Fig. 1. Psycholinguistic cluster profiles in Reddit Depression discourse. (A–E) Bar charts of cluster centroids values: *Plutchik's Primary Emotions*, *PAD Emotional Dimensions*, *VADER Sentiment*, *Textblob Subjectivity*, *Taboo Rate*.

levels of positive emotions like joy and trust compared to C1. Negative emotions and sentiment are less prevalent in C2 (Fig. 1(C)). C2 exhibits lower arousal, higher valence, and dominance (Fig. 1(N)), indicating positive activation and a sense of agency and control (Mohammad, 2018; Posner, Russell, & Peterson, 2005; Stephan et al., 2013). These elements correspond to lower depression levels (Holahan et al., 2005; Knapen, Vancampfort, Moriën, & Marchal, 2015). C2 has also lower taboo rates, suggesting non-aggressive communication, and high subjectivity, indicating a focus on personal perspectives (Gentzkow et al., 2019) (Fig. 1(E,D)).

Topic analysis shows C2 users mention therapy, hobbies, sports, and medications (Fig. 1(b) of *SI*). Specifically, Topics include *Education/Work*, *Family*, *Relationship*, *Friendship*, *Need Support*, *Therapy*, *Happy moments*, *Music*, and *Pets*. *Suicide* and *Self-Harm* are absent. Interestingly, C2's topics and emotions relate to COPE model strategies like *Instrumental/Emotional Social Support*, *Positive Reinterpretation*, and *Mental Disengagement* (Lazarus & Folkman, 1984; Litman, 2006; Litman & Lunsford, 2009). These strategies reflect proactive emotion management and support-seeking from family, friends, therapy and hobbies.

Cluster 3: Balanced/Neutral State. While Cluster 2 exhibits predominantly positive emotions and proactive coping strategies, Cluster 3 (C3) presents a more balanced profile with both positive and negative elements. In fact, Cluster 3 combines sadness, trust and anticipation with average levels of arousal, valence and dominance (Fig. 1(A,B)). Users show a weakly positive VADER sentiment, a lower rate of taboo words and lower subjectivity compared to other clusters, thus indicating minimal personal bias and aggressiveness (Fig. 1(C–E)).

Despite these positive/neutral signals, topic modeling reveals that C3 focuses on technical depression-related terms, discussing topics like *Education/Work*, *Meds/Doctor*, *Self-Harm* and *Suicide* (Fig. 1(c) of *SI*)).

These patterns indicate that C3 users employ both positive coping strategies, like *Seeking Social Support*, and negative ones, like *Self-Harm Coping* (Litman, 2006). Despite a positive and proactive demeanor, support-seeking, and emphasis on therapy, the mention of *Self-Harm* suggests internal conflicts.

Cluster 4: Fluctuating State. Although Cluster 3 maintains a relatively balanced emotional profile, Cluster 4 (C4) shows more emotional variability, characterized by fluctuating patterns of both positive and negative expressions that distinguish it from the more stable nature of C3. Accordingly, as shown in Fig. 1(A), Cluster 4 (C4) users display more sadness, fear and anger and less anticipation than users in C3. C4 users also display moderate levels of arousal, valence and dominance (Fig. 1(B)). C4 users tend to display also more negative VADER sentiment, use more taboo words and display higher subjectivity compared to C3 (Fig. 1(C–E)).

Topic modeling reveals that users in C4 discuss *Relationships*, *Music*, *Education/Work*, *Friendship*, *Pets*, and *Weight* (Fig. 1(d) of *SI*)). These are all activities and entities supporting mental well-being through social support (Krause-Parello, 2012; Raglio, Attardo, Gontero, Rollino, Groppo, & Granieri, 2015). However, professional and medical support is also mentioned in this cluster. Hence, C4 users might be trying to cope with depression by considering heightened arousal activities and coping strategies like mental disengagement.

1.2. Social interactions and online user journeys

We model 4 levels of exposure to a constraining cluster as exemplified in Fig. 2(A). Single and majority of interactions/homogeneous contexts use pairwise links/hyperlinks to quantify the exposure to the target cluster. *Single* means "weak": there is at least one interaction with the target cluster in the users' social circles. *Majority* means "strong": the majority of interactions in users' social circles is with the target cluster. Fig. 2(B) reports the Markov process of the identified statistically significant CTPs.

From the first row of Fig. 2(B), we can observe that conditioning over users in the *High Distress State C1* generates statistically significant transitions only for users in the *Balanced/Neutral State C3*. Interestingly, in the single interaction model, users in the *Balanced/Neutral State C3* can transition to users in the *Positive Resilient State C2* only when interacting with users in the *High Distress State C1* (with a probability of .20). However, in the single homogeneous context model, i.e., when a thread exposes users in the *Balanced/Neutral State C3* to a majority of peers in the *High Distress State C1*, they can transition into the *High Distress State C1* (.25) or into the *Fluctuating State C4* (.41).

Fig. 2(B) second-row underlines that exposure to users in the *Positive Resilient State C2* can lead to statistically significant transitions for users in both the *Balanced/Neutral State C3* and *Fluctuating State C4*. Users in the *Balanced/Neutral State C3* show significant transitions only in the

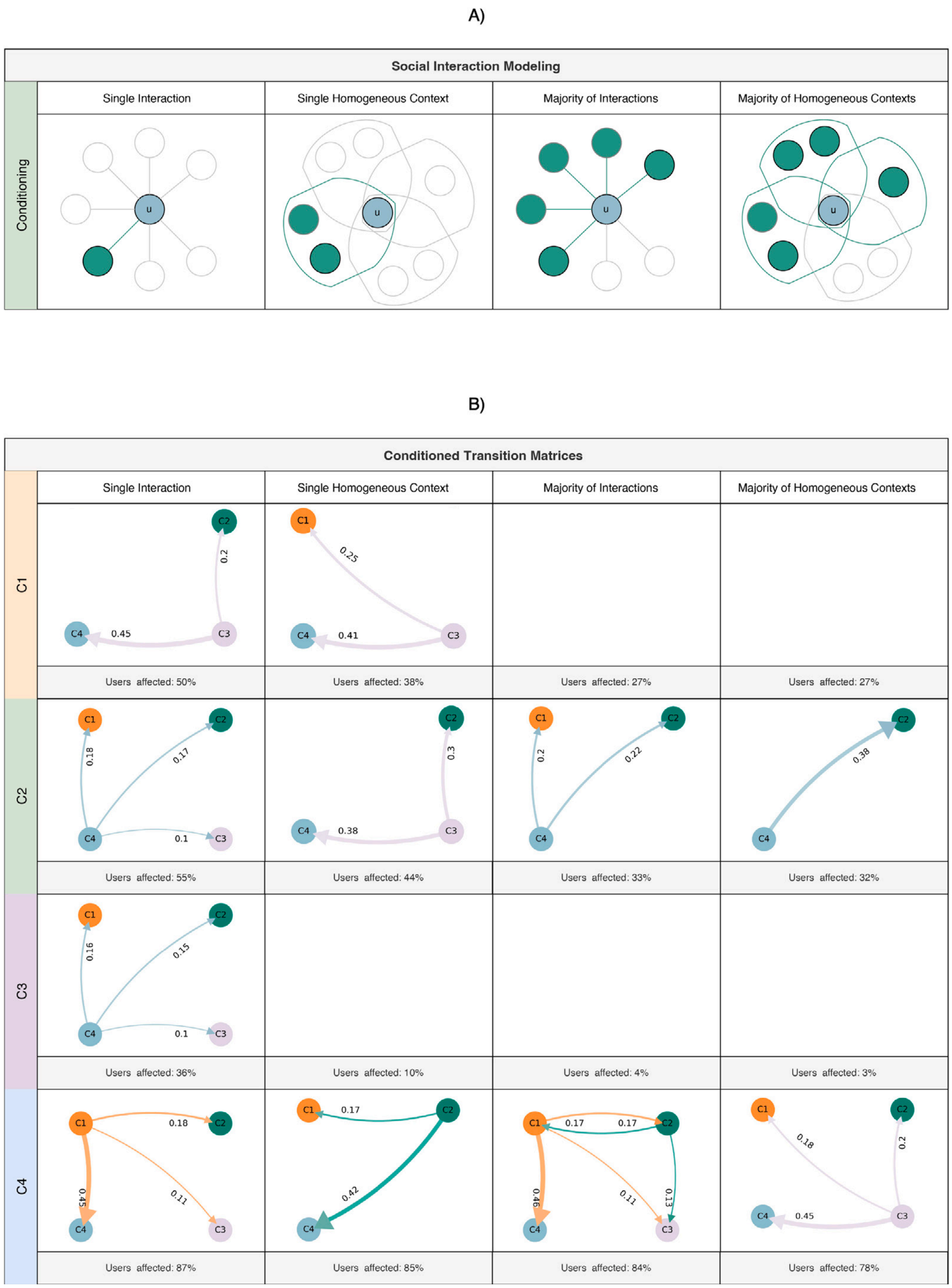

Fig. 2. Social influence and cluster transitions in Reddit Depression interactions. (A) Schematic examples characterizing the four modeled levels of social exposure. Nodes identify users (colored by their profile cluster), and edges/sets identify one-to-one interactions/discussion contexts. **(B)** Visual representation of Markov transition matrices among user clusters conditioned on group-contact typology and filtered based on temporal and volume statistical significance. Rows identify the conditioning profile cluster, and columns the assumed interaction model. In each graph: nodes identify profile clusters; directed edges identify statistically significant transition given the conditioning social interaction with its observed probability; *users affected* identify the percentage of the online population affected by the identified patterns.

single homogeneous context model, where they can transition to the *Positive Resilient State C2* (.30) and the *Fluctuating State C4* (.38). Users in the *Fluctuating State C4*, instead, are strongly affected by interactions with users in the *Positive Resilient State C2* across all exposure levels except for the single homogeneous context model. When users are exposed to content from users in the *Positive Resilient State C2* across all social threads/contexts, we observe a significant transition only for users in the *Fluctuating State C4* (.38). The same transition from users in the *Fluctuating State C4* to users in the *Positive Resilient State C2* is observed also in the single interaction model (.17) and in the majority of interactions model (.22). Moreover, users in the *Fluctuating State C4* display a slight tendency toward moving to the *Balanced/Neutral State C3* (.10 in single interactions) and transitioning to the *High Distress State C1* (.18 in single interactions, .20 in the majority of interactions). These interactions indicate that being exposed to positive content can have a dualistic effect on users in the *Fluctuating State C4*.

Moving to the third row in Fig. 2(B), we observe that users in the *Fluctuating State C4* engaging with content from users in the *Balanced/Neutral State C3* can transition into all other states with analogous probabilities, .16 to the *High Distress State C1*, .15 to the *Positive Resilient State C2*, .10 to the *Balanced/Neutral State C3*.

Finally, Fig. 2(B) fourth-row describes the impact of interactions with users in the *Fluctuating State C4*. Since users in the *Fluctuating State C4* represent the most common profile in our longitudinal analysis, it is expected for them to influence most other users. This is reflected by a higher number of statistically significant transitions and the percentage of users affected reaching up to 87%. For instance, we observe that users in the *Fluctuating State C4* tend to maintain their state even after interacting with other users in the same state. Here, users in the *Positive Resilient State C2* can transition to other states only in single homogeneous contexts and in the majority of interactions scenarios. In both cases, users in the *Positive Resilient State C2* react to content from users in the *Fluctuating State C4* by transitioning to the *High Distress State C1* (.17 in single homogeneous contexts, and .17 in majority of interactions). Once in the *High Distress State C1*, users can transition back to the *Positive Resilient State C2* after being exposed to content from users in the *Fluctuating State C4*, even with single interactions (.18). This and other transitions (see Fig. 2(B)) contribute to a spiral indicating a back-and-forth transition between positive and negative psychological states.

Interpretation of users' transitions

At the level of individual interactions, we find that exposure to content from users in the *High Distress State C1* influences only users in the *Balanced/Neutral State C3*. This is different from our expectations based on the well-known psychological mechanism of online emotional contagion: Kramer and colleagues (Kramer et al., 2014) found that even reading an online post on Facebook can affect the emotional state of readers for a few hours. Instead, our transition findings indicate that the span of negative emotional contagion via single interactions on Reddit is not strong enough to move users discussing depression toward negative spirals. On the contrary, exposure to negative posts can even cause positive shifts, moving users from the *Balanced/Neutral State C3* to the *Positive Resilient State C2* 20% of the time. This finding agrees with past studies (Niehoff & Oosterwijk, 2020) reporting how people may value the sensations evoked by negative content, extracting social value from it while reducing their own uncertainty.

Furthermore, single interactions with users in the *Fluctuating State C4* can move users from the *High Distress State C1* to the *Fluctuating State C4* almost 45% of the time. This effect is almost 3 times stronger than most others observed within a single interaction and thus deserves more attention. We hypothesize such a transition reflects an emotional pattern of the patient journey (Graffigna et al., 2013; Rodríguez-Fuertes, Reinares-Lara, & Garcia-Henche, 2023), where individuals usually deal with pathological conditions, such as major depression, at first mostly through maladaptive/dysfunctional behavior but then move slowly toward acceptance while going through conflict and contrast.

Going beyond pairwise social interactions, exposure to single homogeneous contexts of users in the *High Distress State C1* does not affect users in the *Positive Resilient State C2*, indicating there might be a lack of direct flow between these states. This transition rate, compatible with random expectations, might provide quantitative confirmation of the patient journey (Graffigna et al., 2013; Rodríguez-Fuertes et al., 2023), where moving from negative to positive affect is not instantaneous but rather requires journeying through intermediate emotional states.

We also find that positive online interventions are globally ineffective in improving users' affect. Being surrounded by users in either the *High Distress State C1* or the *Balanced/Neutral State C3* provides no deviations from random expectations. Being surrounded by users in the *Positive Resilient State C2* is similarly ineffective since users in the *Fluctuating State C4* can transition either to the *High Distress State C1* or to the *Positive Resilient State C2* with roughly equal probabilities. Being surrounded by users in the *Fluctuating State C4* can affect users in the *Positive Resilient State C2* but to a considerably lesser extent when compared to homogeneous/coordinated interactions. This difference further indicates that positive states are fragile to fluctuating interactions, which can even cause emotional volatility (Gee, Han, Benassi, & Batterham, 2020) i.e., direct transitions between users in the *High Distress State C1* and *Positive Resilient State C2*. Exposure to content from users in the *Fluctuating State C4* can also massively affect users in the *High Distress State C1*, who can transition to less negative but still variable states (46%).

Discussion

In exploring how online interactions within support communities can impact users' psychological states, our study addresses two core questions: (1) firstly, whether these states exhibit distinct, identifiable patterns aligned with established psychological models; (2) secondly, whether users' progression through these states is linear or follows more complex trajectories.

Our study provides evidence that social interactions discussing depression online – specifically on Reddit – correlate with users' psychological states, as expressed in posts and narratives. To understand the psychological significance of these patterns, we return to the Patient Health Engagement (PHE) model (Graffigna et al., 2013), which offers a structured framework for analyzing how individuals progress through different stages of mental health awareness. Specifically, the user clusters detected in our analysis share notable parallels with the four stages described in the PHE model. Users in cluster C1, expressing a high distress state, demonstrate characteristics similar to the *Blackout* phase of the PHE model. This phase typically manifests through emotional upheaval, a sense of turmoil, and a mix of venting and help-seeking behavior, reflecting the emotional fragility and ambivalence common in early phases of mental health awareness. Users in cluster C2, expressing a positive resilient state, represent individuals with a positive emotional disposition who engage in well-being-promoting activities and actively seek support. This pattern aligns with the *Eudaimonic Project* phase, suggesting resilience and a constructive approach to mental health. We characterize this positive and resilient cluster C2 as the eudaimonically hopeful'' group, reflecting their optimism and proactive coping strategies. Users in cluster C3, expressing a balanced/neutral state, demonstrate a mental health phase marked by cognitive acceptance and adherence to medical support, though internal struggles persist. This corresponds to the *Adhesion* phase of the PHE model, leading us to characterize C3 users as the medically adherent yet conflicting'' group. Users in cluster C4, expressing a fluctuating state, show heightened arousal and negative emotions, often with conflicting views, corresponding to the *Arousal* stage in the PHE model.

In addressing our second research question, contrary to traditional offline engagement models (Graffigna et al., 2013), our findings indicate that online users navigate complex trajectories. Rather than following a direct path from turmoil to acceptance, users' psychological states fluctuate based on exposure to various types of online interactions, including individual replies and longer threads containing conflicting, adherent, or turbulent content exchanges.

Firstly, we found an unexpected pattern regarding positive interactions. Single exchanges with hopeful/positive users from C2 correlate with state changes among users in conflicted states (C4). This pattern appears connected to C4's emotionally polarized nature, where users frequently express suicidal thoughts (Gee et al., 2020). These expressions may indicate higher levels of suicide ideation (Teixeira, Talaga, Swanson, & Stella, 2021) among C4 users. Recent studies have shown how increased levels of suicide ideation correspond with greater emotional volatility (Gee et al., 2020), reflecting a tendency to transition between extreme states of negative and positive affect. This volatility may explain why C4 users struggle to benefit from positive content and often revert to more negative psychological states.

Secondly, we unveiled distinct patterns from individual exchanges when moving to group interactions. Indeed, interactions within homogeneous groups (e.g., discussion threads) showed stronger associations than single interactions, particularly regarding transitions from cluster C3 to C1. This pattern suggests that negative emotional contagion on Reddit requires sustained exposure rather than brief interactions, contrasting with findings from Facebook (Kramer et al., 2014). However, exposure to positive contexts showed mixed effectiveness, correlating with neutral transitions between conflict-ridden clusters (C3 and C4) approximately 38% of the time. This finding underscores the complexity of the patient journey and highlights conflict's central role, even amid positive feedback, as previously hypothesized (Graffigna et al., 2013; Joseph et al., 2023; Rodríguez-Fuertes et al., 2023). The psychological theory of the patient journey suggests that acceptance and hopefulness represent the final stage for individuals managing depression (Graffigna et al., 2013; Rodríguez-Fuertes et al., 2023). However, our findings indicate that C2 does not function as an attractor state — users can and do transition out of it. Exposure to conflicting homogeneous clusters from C4 correlates with transitions to C4 itself among C2 users about 42% of the time. These interactions also associate with shifts from C2 to the negative state of C1 (17% of cases). These patterns suggest that exposure to emotionally polarized and conflicting posts correlates with negative outcomes for users in positive psychological states, a concerning phenomenon warranting additional future research.

Notably, users in the most positive cluster show selective vulnerability — they appear susceptible to conflicting posts while remaining relatively resilient to purely negative content. This difference may stem from two mechanisms. First, hopefulness and positive affect may enhance resilience to negative emotions, as suggested by the psychological theory developed by Tugade and colleagues (Tugade & Fredrickson, 2004). Users might successfully process negative content but struggle with conflicting emotions, which require additional cognitive resources (Litman, 2006). Alternatively, this pattern might reflect coping strategies of avoidance (Holahan et al., 2005), where users maintain hopefulness by avoiding overtly negative content but remain vulnerable to content that appears less threatening yet contains emotional conflict. This phenomenon affects a substantial portion of the community, influencing over 85% of the users on the depression board, warranting attention for future research on posting effects.

These findings demonstrate how integrating psychological content and social interactions can produce relevant psychological insights about the nature of conflict and online social engagement in depression-related subreddits.

Practical Implications. The findings of this work have significant implications for improving mental health support in online environments, informing both platform design, moderation, and clinical practice. First, our observations about non-linear psychological trajectories suggest potential insights for online support systems and mental health professionals. While established psychological frameworks – such as the PHE model – provide structured perspectives on mental health progression (Graffigna et al., 2013), our findings indicate that users' journeys through online support communities may involve varied patterns of engagement. This perspective could contribute to the development of support systems that consider the dynamic nature of online interactions.

Moreover, the observed differences between individual and group interaction effects suggest potential adjustments to community structure and moderation approaches. Our results indicate that sustained exposure within discussion threads shows stronger associations with state changes than individual, one-to-one interactions. Platform designers might consider implementing tools to monitor the emotional content of discussion threads leveraging established theory on emotional contagion and user engagement on social media platforms (Goldenberg & Gross, 2020; Gross, 2015; Kramer et al., 2014).

Additionally, the identified vulnerability of users in positive states to conflicting content points to the potential value of implementing protective features while maintaining user autonomy. Drawing from selective exposure theory (Knobloch-Westerwick, 2014), platforms could develop tools that help users manage their exposure to different types of content. Such features might include content filtering options and graduated engagement mechanisms that allow users to control their participation in more challenging discussions.

Finally, our findings suggest opportunities for enhancing moderator and peer supporter training. Community moderators and supporters should be trained to recognize different psychological states based on linguistic markers, understand the non-linear nature of recovery journeys, and implement evidence-based digital support strategies. This could improve the effectiveness of online support while minimizing potential negative impacts of well-intentioned but potentially destabilizing interactions.

Limitations and Future Directions. This study acknowledges several limitations that pave the way for future research. First, the lack of clinical diagnoses and offline contextual data for online users (such as real-world support networks, life events, or therapeutic interventions) presents challenges in accurately quantifying how users' content reflects distinct psychological constructs like depression, burnout, anxiety, and stress (Fatima et al., 2021; Koutsimani, Montgomery, & Georganta, 2019; Lovibond & Lovibond, 1995). While obtaining such comprehensive data for large-scale studies involving hundreds of thousands of users would be impractical while maintaining privacy, our methodology aligns with recent advances in computational psychology that demonstrate how digital footprints can provide valuable insights when clinical data is unavailable (Fatima et al., 2019; Ferrara & Yang, 2015; Tausczik & Pennebaker, 2010). Future research could strengthen this foundation by integrating additional psychometrically validated approaches.

Secondly, our focus on Reddit raises questions of generalizability. Yet the platform's key features - threaded discussions, community moderation, and anonymous participation - are common across mental health forums (e.g., TalkLife,[11] 7 Cups,[12] Mental Health Forum[13]), suggesting potential broader applicability that future studies should verify.

Additionally, two methodological considerations warrant attention. First, our approach of aggregating users over time periods potentially conflates individual emotional trajectories into single averages. Although this choice prioritized identifying global patterns in an unexplored online board, future studies should explore finer, time-based analyses of individual trajectories. Second, while mapping our clusters to PHE model stages (Graffigna et al., 2013) is supported by quantitative methodology, it may oversimplify the complexity of psychological transitions, as these states exist on a continuum rather than as discrete categories.

Finally, our framework's language-agnostic approach to topic modeling, while offering versatility, may miss important context-specific nuances in depression-related discourse. The way certain concepts and ideas are perceived within mental health communities may differ significantly from their use in general language (Teixeira et al., 2021). The development of context-aware analysis frameworks could better account for depression-specific language use and its nuances in future research.

[11] https://talklife.com/

[12] https://www.7cups.com/forum/

[13] https://www.mentalhealthforum.net

CRediT authorship contribution statement

Virginia Morini: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Salvatore Citraro:** Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Elena Sajno:** Writing – original draft, Validation, Investigation. **Maria Sansoni:** Writing – original draft, Validation, Investigation. **Giuseppe Riva:** Writing – original draft, Validation, Supervision, Investigation. **Massimo Stella:** Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Giulio Rossetti:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.chbr.2024.100542.

Data availability

I have shared the link to my data/code.

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