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Modeling and Assessing the Temporal Behavior of Emotional and Depressive User Interactions on Social Networks

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ABSTRACT The way users interact on social media can indicate their well-being. When depressed, people's feelings tend to be more evident, affecting how users interact and demonstrating their feelings on social media. This paper presents a new approach for the temporal assessment of emotional behavior and interaction among depressed users on social networks. We start by modeling user interactions using complex networks, grouping users through time using the Clauset-Newman-Moore greedy modularity maximization. We evaluate the built networks using metrics such as assortativity, density, clustering, diameter, and shortest path length, closeness, and coverage. Then, we propose EMUS, a method for establishing an emotional user score based on the extraction of emotional features in texts of posts and comments. To extract emotional features, we combine the use of the Empath framework and VADER lexicon. Finally, based on the standard deviation among users, we establish a metric for assessing mood levels. We evaluated users for 33 days, and the results show a sequence of mixed emotional behaviors with high correlations between the number of active users in the network communities, and the form and quality of interactions. The developed approach can be further applied to other database graphs, for different sequential pattern analysis and text-mining contexts.

INDEX TERMS Affective computing, behavior analysis, complex networks, data mining, depression, emotion recognition, user interaction, sentiment analysis, social media, social networks, text mining, temporal analysis.

I. INTRODUCTION

Online social networks have become an increasingly natural environment for sharing opinions and feelings, being actually part of people's daily lives. Different social factors and contexts are supported by the use of social networks, such as presented in collaborative works [1], learning [2], relationships [3], and dating [4]. Today, it is common to first meet someone on a social network and afterwards meet him/her in person [5]. Moreover, when a connection first occurs in the

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real world, it is later consolidated in the virtual environment, even as a sign of mutual approval and interest in maintaining a relationship [6].

People have included social media in their routine, whether for personal or professional use, causing a feeling that life does not have the same meaning without online interactions. The researchers in Affective Computing, an area of science formed by researchers of Computing and Emotions, have explored social media as another lens to model and evaluate emotional behaviors. In Affective Computing, several state-of-the-art technologies and methodologies for various contexts have been developed to (i) understand and model human behavior, predict emotions and mental disorders, as in [7]–[11]; or (ii) consider emotional aspects in the design of intelligent systems [12]–[14].

The study and recognition of emotions started long ago with Darwin and Prodger [15], way before the computers and integrated systems emerged. In this work [15], Darwin investigated children's facial expressions as they interact with their peers, blind or sighted, and persons with disabilities. Darwin founded evidence from some observations that facial expressions corresponded to particular emotions, regardless of each individual's environment. Later, Ekman *et al.* [16], [17] explored the recognition of a set of emotional expressions that could be universally representative and free from cultural bias. Contemporary advances in behavior analysis and new protocols and methodologies have made it possible to assess mood disorders, behavioral, and mental health issues.

Depressive disorders have been a recent research concern in the field of Data Science [18], especially after the discovery that data mining approaches can assist in the diagnostic identification and treatment of depression [19], [20]. In a previous study [21], we provided an extensive discussion about recognizing depressive mood disorders in social networks using machine learning and sentiment analysis. The work presents and discusses the appropriate techniques for specific media, such as text, images, videos, emoticons, and specifics social media platforms.

People with depression (major depressive disorder) commonly experience persistent feelings of sadness, thoughts of worthlessness or guilt, loss of interest in previously pleasurable activities, agitation or psychomotor delay, among other symptoms [22]. Besides, symptoms can vary from mild to severe, with an incidence of approximately 7% in the United States, with a more significant number of women diagnosed and individuals between 18 and 29 years old [23], affecting more than 264 million people worldwide [24].

The Pan American Health Organization (PAHO) [25] informs that a large proportion of depressed people do not receive adequate diagnosis and treatments, and many do not seek health services for this reason. In contrast, social media is accessed by people with different behavioral characteristics, including people with depressive disorders, and has become a rich source of health information [18], [21], [26].

Many people experiencing varying degrees of suffering take advantage of virtual platforms to share feelings with others, relate, receive social support, and express their emotional state, especially feelings of helplessness and insecurity [19]. Choundhury *et al.* [19] followed user's posts on Twitter using the crowd-sourcing methodology. They identified behavior patterns (negative affect, reduced active participation, highly clustered ego networks, occupational activities, relationship concerns, drug treatment, and expressions with religious content) of people who were diagnosed with depression. In [27], Vedula *et al.* observed the same behavioral patterns and the predominance of nighttime activities on the network, characteristic linguistic styles (*e.g.*, use of self-centered pronouns), and little or no exchange of influence between depressed users and their egocentric network over time. The results indicated that a polarity of negative feelings could be established among depressed users and intense proximity between users with similar problems.

The structural position of users on a social network, and their transitivity (if their friends are friends with each other), and centrality (whether they are located in the center or at the edge of the network), can influence the development of characteristics and behaviors among them [28]. Rosenquist *et al.* [28] shows a probability of 93% of a user being depressed if they are directly connected to a depressed person (a friend on social media). Similarly, there is a probability of 43% that a user is depressed if there are two degrees of separation between them (friend of a friend). The probability decreases to 37% if the connections are with three degrees of separation, *i.e.* it is a friend of a friend of a friend. The study also indicated greater severity of symptoms of depression among those located at the edge of the network and a lower score on the depression scale using the Center for Epidemiological Studies Depression Scale, CES-D [29] for those centralized in the network.

While social ties can have a salutary effect on individuals' mental health and psychological well-being, they can also compromise their health. Face-to-face emotional support was observed in the study [30] as a protective factor in the development of depression (effect size, 43%). In contrast, social support established in social networks was associated with an increased risk of developing the disorder (effect size, 20%). Considering the exponential increase of users on social networks in recent years [20], evaluating the network structure and its impact on users' mental health has been of interest to several researchers in the area.

The literature has explored how relationships take place on social networks and how to conduct an analysis of feelings regarding individual posts and comments. However, it is understood that, for a health assessment and mood disorders such as depression, it is necessary to observe users' interactions and feelings for a more extended period, instead of a single post as most studies consider. This approach can lead to the assessment of changes in the expression of feelings.

This work aims at assessing how interactions between depressive users occur in the social network environment, as well as their correlation with users' emotional expressions. Thus, we investigated and combined the use of algorithms and metrics of complex networks and the extraction of emotional characteristics from the text using two lexicons. Accordingly, we aim at answering the following research questions:

1) *How does the interaction between depressive users on the social network occur? Are there behavioral and emotional changes over time?*
2) *Is there a correlation between interaction and emotional behavior patterns among depressive users in online social networks?*
3) *Can social networks be a suitable environment for mutual support between depressed users?*

To answer the research questions above, we highlight the following contributions:

- We model and assess the interaction behavior of depressed users on social networks using complex network approaches and evaluation metrics.
- We propose and build a method to extract emotional characteristics and polarity of feelings, which serves as an indication for establishing an emotional score of the user. For this, we explore text-mining, lexical approaches, and a pre-trained neural network model.
- We evaluate the correlation between the characteristics of the interactions and the features of emotional expressions extracted from the posts.

Paper Outline: This paper is organized as follows. Section II presents the materials and methods, including text-mining, complex networks, analysis of feelings, and the extraction of emotional characteristics from posts. Section III presents the results. Section IV discusses the results by listing the findings using computational metrics and their contributions to behavior analysis. Finally, Section V gives the final remarks.

II. MATERIALS AND METHODS

In this section, we detail methods and materials used in each stage of the process: data collection and description of users; the modulation of the user's interactions of the social network through complex networks and the detection of communities; the metrics used to assess and respond to specific aspects of the interaction behavior among depressive users; the approaches used to extract topics discussed in the communities and to recognize feelings and emotional characteristics. All steps are detailed in the following subsections.

A. DATA COLLECTION AND USER DESCRIPTION

The Reddit social network has specific communities and flexible privacy terms for data collection. In contrast, Facebook and Instagram have more restrictive privacy policies regarding user posts' collection. Twitter does not have much personal information [31], such as sharing feelings and emotions, is used mainly by mass communication operators (TVs, radios, business's marketing, and newscasts) or famous people, *e.g.*, politicians, artists, and singers. Accordingly, we developed a data crawler using the official Reddit API[1]

The chosen community is very active on Reddit, having more than 713k members and around 1k online users every day. The forum is where the users post, interact using upvotes and downvotes, and insert comments in a hierarchical structure. Given this study's purpose, which considers a temporal evaluation, the most significant difficulties found were (i) finding users who posted regularly and (ii) remained active for 33 consecutive days or more. According to this restriction, for this study, we select 1,212 frequent users that posted for 33 days, with at least one post every three days.

To assess the temporal evolution of a user's behavior in the groups, our database was divided into ten shifts, which refer to 11-time windows with three days each, a total of 33 days of monitoring. To understand the level of depression in the chosen social media community, we conducted a survey based on the DSM-5 Level 2—Depression—An Adult questionnaire provided by the World Health Organization. To answer the questionnaire, the user anonymously needed to click on the acceptance term. We asked the users about how they felt 30 days ago, 15 days ago, and in the present moment to observe behavioral and emotional changes. The users selected one item from a set of options (never, rarely, sometimes, often, always) for each expression. The expressions are: (i) I felt worthless; (ii) I felt that I had nothing to look forward to; (iii) I felt helpless; (iv) I felt sad; (v) I felt like a failure; (vi) I felt depressed; (vii) I felt unhappy; (viii) I felt hopeless.

It is worthwhile to mention that the collection process and all the methodology described in this section were automated and followed the protocol approved by our institute's ethics committee, whose registration is provided at the end of this manuscript.

B. MODELING USER INTERACTION USING COMPLEX NETWORKS

In complex networks, the term network describes an object composed of elements and the connections between them. Using a social network as an example, the elements are usually associated with people (users), while the connections can be associated with their friendly relationship. Mathematically, the natural way to model these networks is from the graph theory [32].

A graph or network $G = (V, E)$ is a mathematical structure composed of two finite sets V and E, where V is the set of n vertices (or nodes) and E is the set of edges (or connections) of the graph. Each graph vertex is normally identified by an integer ordered value $i = 1, 2, \cdots, n$, while the connection between two nodes i and j are represented by (i, j), *i.e.* $E \subseteq (i, j) \mid i, j \in V$. According to the type of edge allowed, graphs can be classified into directed, non-directed, or mixed [33].

[1] The Reddit API documentation is available in www.reddit.com/dev/api/ to collect posts from a mutual-support sub-reddit community addressing depression (entitled `r/depression`). In the API, we made a REST requisition, defining the community of interest.

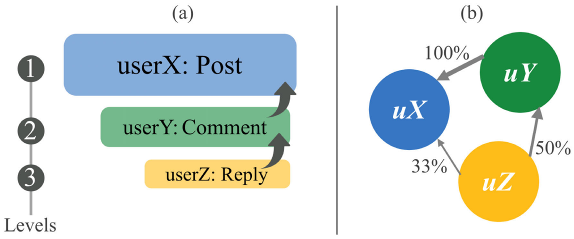

FIGURE 1. Proposed modeling for (a) post's hierarchy and (b) interactions' weights.

To evaluate the interaction behavior among depressive users, we modeled the interaction of users as a complex network. Figure 1 illustrates the hierarchy and how it is modeled as a network. In the social media context and this study, it is understood as an interaction when a user interacts with another user's post, for example, by commenting on it. Then, given that user X commented on user Y's post, a connection is created between the two users by a directed edge of type $X \rightarrow Y$. As this is a direct interaction (post → comment), we assign the maximum weight of 100% for this level of interaction in our modeling. Given that the user Y replies on a comment of user X, a directed edge is created with a weight of 50% (*i.e.* 100/2) in the form $Y \rightarrow X$. We consider this a direct, but secondary interaction in our modeling (comment → reply) since the reply is indirectly connected to the main post. Furthermore, the reply and the main post are connected using an edge in our modeling due to the indirect interaction between users, which receives a weight of 33% (*i.e.* 100/3). In summary, the edge's total weight is divide by the level located in the post hierarchy.

C. ASSESSING THE USERS' INTERACTIONS USING COMPLEX NETWORKS' METRICS

We applied the Clauset-Newman-Moore greedy modularity maximization method introduced by [34]–[36] to detect communities in the graph. The greedy modularity maximization method starts interactively with each node in its community and joins the pair of communities that have the most potential to increase its modularity until this pair no longer exists. Although the original method does not consider the edges' weight, we adapted the method to consider having an assessment close to the possible social network environment. In this study, we assume that a user has a closer relationship with those who he/she interacts directly with.

The temporal behavior analysis of networks and communities were modeled in 3-day shifts, along 33 days, and we applied the following metrics to evaluate the interaction for all networks in each shift, as well as each community:

- **Assortativity Degree (AD):** Assesses the similarity between nodes in a network [37]. The coefficient is the Pearson's correlation between linked nodes, and is typically between -1 and 1, where 1 is considered to have perfectly ordered mixing patterns, and -1 means that the network is totally dissimilar. When AD is positive, nodes tend to connect to other nodes with similar properties within a network. When AD is negative, it indicates nodes' tendency to connect to other nodes with different properties within a network [38]. We can understand AD as how depressed users interact with people with similar interaction profiles in our context. It is how practical the network or the community is concerning being a good mutual support environment for depressive user groups.
- **Density (DS)**: Shows how complete the network or community is [36]. Considering v is the number of vertices and e is the number of edges in G, the density d of a directed network is defined as:
$$d = \frac{e}{v(v-1)} \tag{1}$$
In practice, the Density describes how many potential connections are real connections in a network. A potential connection may or may not exist. For example, user A may know user B. In contrast, the actual connection exists: user A knows or is directly connected to user B. To illustrate, in a family home, the actual connections must be 100%, as everyone knows each other. However, at a train station in a large city, close and authentic connections are expected to be low. This metric answers: how well do depressives know each other, or are they directly or intimately connected?
- **Average Clustering (AC):** Measures the degree to which the nodes of a graph tend to cluster [39]. Evidence suggests that the nodes of most real-world networks, and especially social networks, tend to create cohesive groups characterized by a high density of ties [40]. Grouping is a widespread property on social networks, referring to circles of friends where members know each other, thus forming a group on the network. If a node A is connected to B, which in turn finds itself connected to C, there is a high probability that A will also be connected to C [40]. In this study, the density indicates: (i) *"how strong the connections between groups of depressive users are?"* and (ii) *"what is the potential of grouping these users?"*
- **Diameter (DM):** The maximum eccentricity, that is, the greatest distance between any pair of vertices. To find the graph's diameter, we find the shortest path between each pair of vertices, and then we verify the greatest path length of the graph [40]. In this study, this metric indicates the maximum distance that one user would be from the other on the network.
- **Average Shortest Path Length (SPL)**: This metric shows the average number of steps during the shortest path length for all possible pairs of network nodes. It is a measure of the efficiency of information or mass transport in a network [40]. In this context, the average number of people a user will have to talk through to contact an unknown person and how easy the discussing topics can flood the network or group.

Further, to analyze the entire network and the quality of detected communities, we counted the number of communities and use the following network metrics:

- **Coverage Community Generation (CCG):** The ratio between the number of intra-community edges to the number of nodes in the network. The plurality of edges is computed if the Graph is a multigraph [41].
- **Community Generation Performance (CGP):** The ratio of intra-community connections with the total number of possible edges, plus inter-community non-edges [41].
- **Community Growth Behavior**: We evaluate the growth of the C_i^j community between two time windows $j-1$ and j as follows. We obtain the absolute number of users present in a given community in the first $|C_i^{j-1}|$ and second $|C_i^j|$ windows. The index calculation is introduced by [42], [43]. The equation is defined as follows:

$$\mathrm{GR}(C_i^j) = \frac{|C_i^j|}{|C_i^{j-1}|} - 1 \tag{2}$$

- **Temporal Dynamic of communities using F-Score:** We evaluated the permanence (fidelity) of users in the same C_i community over time using the F-score metric, modeling as follows. Let C_i^j be the set of users in community i and at time j. We model the precision and recall between the $j-1$ and j windows as:

$$\mathrm{Precision}_i^j = \frac{|C_i^{j-1} \cap C_i^j|}{|C_i^j|} \tag{3}$$

$$\mathrm{Recall}_i^j = \frac{|C_i^{j-1} \cap C_i^j|}{|C_i^{j-1}|} \tag{4}$$

$$\text{F-score}_i^j = \frac{2 * Precision_i^j * Recall_i^j}{Precision_i^j + Recall_i^j} \tag{5}$$

D. OBSERVING USERS' VERBAL AND EMOTIONAL BEHAVIOR

To establish and assess the context and emotional conditions of the users, we propose the EMUS (**E**motional **U**ser **S**core) method. EMUS works as follows: For each 3-day shift in time, we model the complex network of user interactions and then calculate the user's emotional score, extract contextual characteristics from the conversations, and identify the most common emotions that each user demonstrates through their posts and comments.

Algorithm 1 receives the user's current score as input, which starts with zero if the user has no previous posts and comments. The algorithm outputs the updated user emotional score, the subjects discussed, and the identified emotions. EMUS starts with each new post or user comment (line 2). Function *estimateNegatives* (line 4) aims at estimating the semantic orientation of negative expressions. For this, we used the VADER lexical analyzer [44]. VADER is a dictionary of words annotated by the semantic orientation of the feelings that go from -1 to 1, from negative to positive. In this task, we accumulate the values of the semantic orientation of the negative expressions found in the posts' content. Function *estimatePositives* (line 5) performs the same procedure as before, but accumulates the semantic orientations of positive words and expressions. In line 7, EMUS builds a bag of emotions (`userEmotions`). We use Empath, a lexical analyzer based on a trained neural network with 1.8 billion fiction stories for the recognition of emotions [45]. From such word embedding, the program generates a vector space that tests word similarity, uses seed concepts to identify and find new terms for each of its classes, and filters its classifications utilizing crowdsourcing [45]. At this stage, we consider the Empath categories of emotions (positive and negative emotion) validated by humans and information about the context in which the emotion is present, such as work, studies, addictions, and pain.

The *userScore* is calculated based on the accumulation of polarities over the user's timeline. For example, if the user posts something positive with valence +55, and later something negative with valence -30, the *userScore* of the user is +25. This calculation is performed at line 9 of Algorithm 1, where the user score is updated.

Algorithm 1 The EMUS Method

Input: userScore, userPosts, userComments
Output: userScore, userEmotions

1: Initialization
2: **for each** new post or comment **do**
3: `Identify positive and negative emotions`
4: sNeg ← *estimateNegatives*(userPosts, userComments)
5: sPos ← *estimatePositives*(userPosts, userComments)
6: `Compose bag of user emotions`
7: userEmotions ← *getEmotions*(userPosts,userComments)
8: **end for**
9: userScore ← sNeg + sPos ▷ `Compute user score`
10: **return**(userScore, userEmotions)

III. RESULTS

A. DESCRIPTION OF ACTIVE USERS

Three hundred fifteen users answered the survey, which was available for 15 days in the virtual community analyzed in this study. Out of 315 users, 45% are in the 18-24 age group, 25% in the 12-17 age group, 24% are in the 25-34 age group, 4% are 35-44 years old, 1% are in the 45-54 range, and 1% are in the 55-64 age group. In total, 57.8% of users reported being male, 37.1% female, 3.5% did not report, 0.9% reported being non-binary or gender-fluid. Regarding race, 64% of users informed to be White, 19% Asian Pacific Islander, 8% Hispanic or Latino, 5% Black or African American, 4% other, and only one person informed to be Native American or American Indian.

Regarding their feelings, using the T-Score scale of the PROMIS of depression for adults (level 2) [23], as Figure 2 shows, 30 days before answering the survey, 61.30% of the respondents were classified in Severe depression, 35.9%

TABLE 1. Network behavior of depressive user interactions over time. The table shows the network characteristics in different windows (shifts from 0 to 10) of 3 days each, totalizing 33 days of sequential tracking.

Network Metrics	Day Shift										
	0	1	2	3	4	5	6	7	8	9	10
Assortativity Degree	0.034	0.241	0.091	0.055	0.096	0.13	0.045	0.11	0.15	0.06	0.30
Density	0.014	0.015	0.013	0.015	0.013	0.017	0.011	0.011	0.014	0.012	0.019
Average Clustering	0.33	0.33	0.34	0.31	0.33	0.32	0.33	0.31	0.31	0.36	0.31
Diameter	8	8	8	9	8	8	8	7	9	8	8
Average Shortest Path Length	3.77	3.56	3.77	3.44	3.67	3.51	3.79	3.52	3.61	3.83	3.51
Community Generation Performance	0.87	0.84	0.89	0.88	0.88	0.86	0.87	0.85	0.87	0.89	0.76
Coverage of Community Generation	0.86	0.83	0.85	0.79	0.83	0.84	0.84	0.76	0.85	0.80	0.87
Number of Communities	10	9	9	12	13	11	12	10	12	16	7

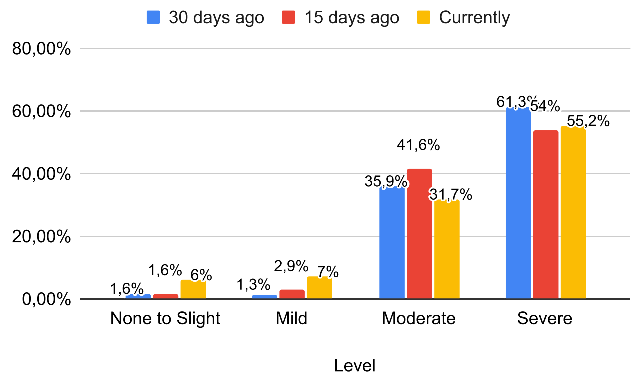

FIGURE 2. Depression level users answered the survey about their sentiments for 30 and 15 days ago and currently.

Moderate, 1.3% Mild, and 1.6% None to Slight. Over 15 days before, the results showed 54% in the Severe category, 41.6% in the Moderate category, 2.9% Mild, and 1.6% None to Slight. When they answered the survey about the current feelings, 55.2% were classified as Severe depression, 31.7% Moderate, and 6% None to Slight.

B. NETWORK MODELING

Figure 3 shows the changes on the modeled network, considering every 3-day shift, from day 1 to day 33, resulting in 11 shifts in time. Every community is highlighted using a different color. Notice that the active users from each community form clusters that are highly interconnected. Also, the number of detected communities changed from a day shift to the other, but seven were modeled at every day shift, which we call the Top-7 Communities. It is worth mentioning that communities are dynamic. They move on the network and change their shape, subjects, and users over time. Also, they can segregate and even cease to exist to the point that new communities emerge. Respecting aspects of privacy and considering that we focus on group analysis in this research, we do not precisely monitor users' paths between communities.

Table 1 shows the metrics extracted from the built networks for everyday shift considered in our modeling. Figure 4 presents the Pearson's correlation matrix among the different metrics from Table 1, where intense colors correspond to high correlation (positive or negative) among the metrics. The Average Shortest Path Length (SPL) values were strongly correlated with the Average Clustering (AC) method, indicating that there is a proximity of users along the interactions on the networks, which in consequence tends to create cohesive groups of users communicating with each other and creating cycles (*e.g.*, User$_a$ interacts with User$_b$, which in turn interacts with User$_c$, which probably interacts with User$_a$). The Community Generation Performance (CGP) and Assortativity Degree (AD) also presented a high correlation. Therefore, the ratio of intra-community connections, considering the number of edges (*i.e.* interactions among active users), was correlated with the connections between users presenting similar properties within the network. The intra-community connections have also shown high correlations with the Number of Communities (NC) and the network Density (DS), which informs how complete the network or community is. These results inform us that the virtual environment of mutual support for depressed users will perform well when the quantity, quality, and form of friendships (connections) are similar. That is, the greater the similarity between users, the better the community. Besides, the denser the network and the more communities, the greater the intra-connections, positively impacting the environment's performance.

C. TEMPORAL EMOTION ANALYSIS PER COMMUNITY

In this section, we describe the temporal emotion analysis over the detected communities of our modeling. We employ the classifications of posts provided by the Empath framework [45], identified as positive or negative emotions, and categorize the interactions among active users. Table 2 lists the expressions of emotions in the positive and negative categories. Following, we analyze the temporal changes of emotions identified in posts, considering the top-7 communities of the built network and the classifications provided by Empath, considering the subjects discussed within the communities. We selected only seven communities because it was the highest number of communities present in all-day shifts.

Figure 5 shows the occurrence of positive and negative emotions (and the combination of both, which we call mixed emotions) among the top-5 classifications obtained by Empath, at every 3-day shift, and for the top-7 communities. Empty spots occur when Empath did not classify the community content as containing positive or negative emotions at the corresponding day shift.

Community 1 had the most significant number of engaged users throughout the studied period, presenting an increasing trend: it started with 166 users and finished with 439. During the first five time shifts, the conversations contained mostly negative emotions, for example "shame", "sadness",

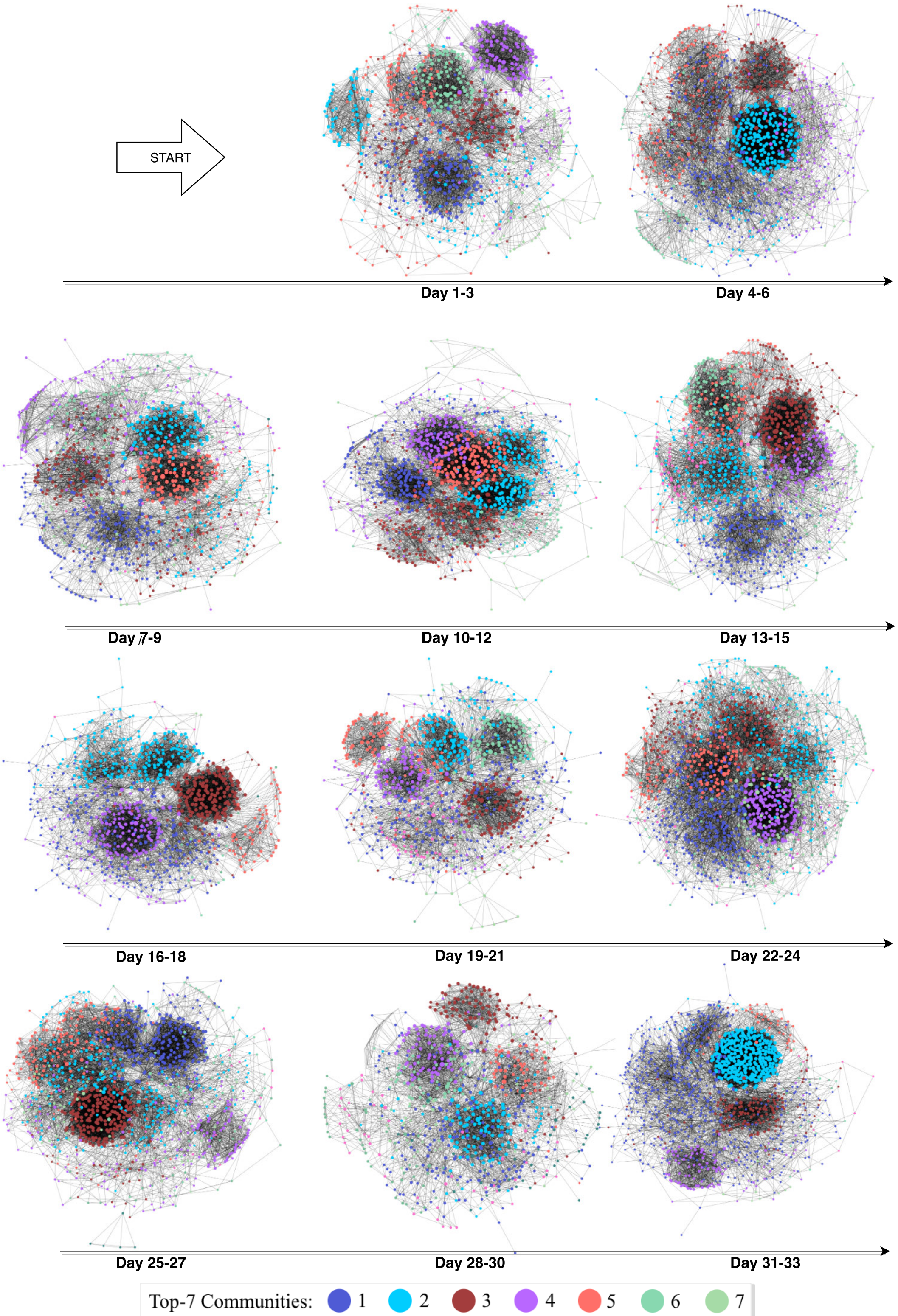

FIGURE 3. Complex Network and its communities every 3-day shift.

"pain", "violence", "suffering", and "death" emotions. The approach did not classify the feelings from days 16-18 as positive or negative, but identified mixing emotions: "love", "contentment", "optimism", "pain", and "shame". In the two time shifts classified as positive, the most frequent patterns identified were related to "achievement", "pride", "heroic", and "optimism". Despite the two positive time shifts, the community has focused on posts and replies

TABLE 2. Words from the positive and negative emotions' categories, provided by Empath.

Positive Emotion
happiness, enlighten, better, enthusiasm, pride, joyful, compassion, dearly, forgiving, kindness, bravery, closure, thrill, honestly, triumph, bond, honesty, alive, concern, reunite, joy, surprise, forgiveness, assurance, sympathize, understanding, reason, rejoice, care, faith, great, empathy, certainty, keep, trustworthy, affection, cherish, emotion, love, family, trusting, respect, trust, gratitude, confidence, adoration, friend, happy, overjoyed, determination, reassurance, glad, loved, admiration, wish, accomplishment, optimism, excitement, convince, hope, freedom, feeling, eagerness, willingness, sincere, sincerity, honest, genuine, comfort, elation, thrilled, loyalty, curiosity, unconditionally, proud
Negative Emotion
violent, kill, hell, hate, dying, death, thinking, hated, crying, surprised, hurting, worse, beat, stop, crushed, break, worst, trouble, disappointed, killed, lost, cry, worried, worst_part, bad, stupid, either, die, mean, insane, fucking, scared, hard, dead, beaten, horrible, monster, weak, loose, threatened, punch, killing, blame, reason, so_much_pain, hurts, losing, wanted, pissed, care, scary, accident, fault, guilty, terrible, swear, last_straw, heartbroken, scare, seeing, drunk, terrified, freaked, raped, frightened, poor_girl, lose, angry, fight, poor_guy, hurt, ashamed, depressed, unthinkable, tortured, crazy, confused, sad, hit, alone, lie, afraid, dying, shocked, angered, sick, badly, pain, react, wrong, mad, upset, fighting, furious

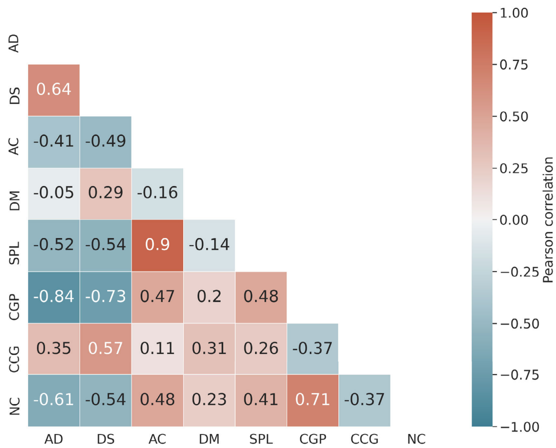

FIGURE 4. Correlation matrix of the network metrics (considering all communities).

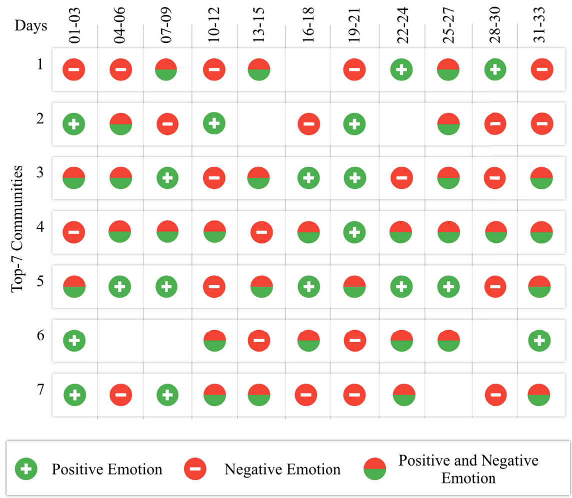

FIGURE 5. Identification of positive and negative emotions in the top-7 communities, at every 3-day shift.

containing mainly negative emotions, in general. This behavior was similar to the one identified in *Community 4*.

Community 2 started with posts reporting positive emotions related to "love", "friends", "optimism", "affection", interleaving time shifts containing few negative emotions related to, for instance, "death", "suffering", and "violence". The last time shifts of this community contained mainly negative emotions, including "nervousness", "pain", "shame", "violence". *Community 3* also presented an interleaved positive and negative emotion pattern, but with a few distinct classifications: "children", "wedding", "optimism", and "celebration" related to time shifts classified as positive emotions, and "contentment", "pain", "masculine", and "communication" related to time shifts classified as negative emotions. Literature data are similar in pointing out that people with depression tend to have more significant negative emotions on social networks [46], [47]. However, some studies highlight the ambivalence of emotional expression, resulting from an internal conflict between the desire to express the negative emotions experienced and the fear of expressing them due to consequences, such as rejection, criticism, or humiliation, among others [48], [49]. Therefore, depressive people may be able to inhibit negative emotions at various times. Besides, they do not always express negative feelings, as they may have mood swings depending on the severity of the symptoms [47], or even express positive emotions when providing words of encouragement to other network users. Another point observed is the influence that one person can have on the other in social network interactions [28]. As observed in community 2, people who initially expressed positive emotions may have been impacted by other network users, which started to increase negative emotions until the end of the data collection.

Although interleaving time shifts with positive emotions with two time shifts related to negative emotions, interactions from *Community 5* presented content related with positive emotions mostly. The positive terms classified include "optimism", "achievement", "party", "heroic", "pride", "wedding", "family", "love", "celebration" and "friends". The negative terms include "shame", "pain", "violence", and "suffering".

The time shifts from *Community 6* presented the majority of negative emotions, except for the first and last time shifts. Interactions among users from this community focused on themes related to "work", "college", "economics", "business", "occupation", "cooking", "eating", which mostly do not directly relate to emotions. However, the characteristics found in community 6 emphasize the importance of observing the context in which the user is inserted and its potential impact on emotions, especially regarding work and educational contexts. These characteristics may also be related to occupational activities ("work", "occupation", "cooking", "college"), and financial ("economy", "business"), and may have stood out for being the target of concern in people with depressive symptoms [19]. Further, users from Community 6 also had conversations classified as "nervousness",

TABLE 3. Identified emotion transitions (without considering mixed and absent identifications), and the top classified term at every day shift.

Top-7 Commun.	Emotion transition	Top classification per shift
1	negative → positive → negative	shame; friends; pain; school; friends; love; family; achievement; family; hygiene; shame
2	positive → negative → positive → negative → positive → negative	love; death; speaking; achievement; health; play; optimism; pain; optimism; payment; nervousness
3	positive → negative → positive → negative	optimism; violence; optimism; shame; shame; optimism; party; speaking; pain; shame; pain
4	negative → positive	messaging; shame; speaking; pain; suffering; shame; optimism; violence; pain; speaking; appearance
5	positive → negative → positive → negative	pain; optimism; optimism; home; friends; optimism; communication; achievement; optimism; speaking; friends
6	positive → negative → positive	achievement; work; cooking; hygiene; pain; optimism; pain; trust; phone; nervousness; optimism
7	positive → negative → positive → negative	party; pain; optimism; celebration; optimism; pain; sleep; optimism; pain; sadness; celebration

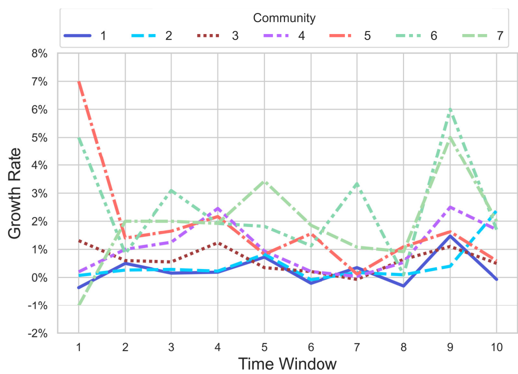

FIGURE 6. Communities growth evaluation.

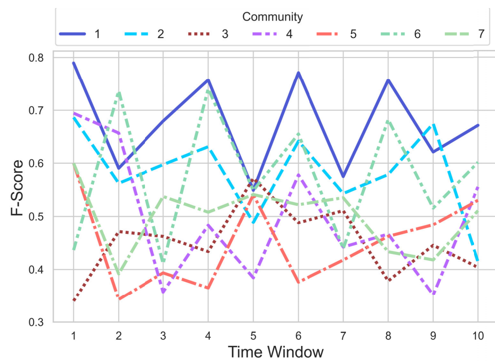

FIGURE 7. Dynamic community evaluation using F-score.

"pain", "achievement", "pride", "heroic", "shame", and "optimism".

Finally, *Community 7* was the only one that started with interactions identified as containing positive emotions and finished with predominantly negative emotions. The initial positive emotions relate to the classifications "party", "celebration", "optimism", "optimism", "love", and "trust". On the opposite, the negative emotions mostly related to "shame", "nervousness", "work", "violence", "pain", and "sadness".

Table 3 lists the emotion transitions over the day shifts, considering only positive and negative classifications, for every community. The subjects discussed within the communities were diverse (*e.g.*, family, work, cooking, party). Nevertheless, none of the communities presented a steady emotional pattern (*i.e.* only positive or only negative emotions). This observation characterizes the dynamics between interactions of users identified as depressive in our modeling.

Regarding the Community Growth Behavior defined in Section II, Figure 6 shows the growth community rate over time. It is possible to observe that the average relative growth is 0.97% over the 11-time windows, that is, with no significant variation. Nevertheless, the shift 8 → 9 presents an expressive growth in all communities. Compared to the demonstration of emotions and feelings on days 28 → 30 depicted in Figure 5, the sum of the polarity presents greater negativity among all communities. The drop in the growth rate of the communities (shift 8) is related to the most significant number of positive expressions.

Concerning the temporal dynamic of communities using F-Score (defined in Section II), Figure 7 shows the percentage of active users who remain in the same community between periods. A low F-score means a high exchange rate between the target community and the rest, while a high F-score indicates that users are part of the same community. Regarding the top-seven communities analyzed, there is a significant exchange of active users between the communities. Regarding users' continuous permanence, community 5 maintained the lowest level of engagement with an F-score below 0.50. Likewise, communities 5 and 6 also had low rates in most periods. In comparison to Figure 7, it is clear that these communities that did not have high engagement mostly show positive feelings in the same period, considering the sum (polarity score). The communities with the most prolonged stay of active users (1, 2, and 6) have a greater expression of feelings of negativity. It is possible to conclude that, in addition to users obtaining more effective communication and closer relationships on the network, the results suggest that they engage more in negative or even depressive topics. This is evident, mainly by community 7, which maintained a medium engagement since it showed mixed feelings. With that, it is possible to conclude that depressives are more engaged in negative topics, and that positive topics cannot engage depressive people in the same way.

D. EMOTIONAL USERS SCORE

Figure 8 shows the computed emotional score results for users analyzed using our proposed method EMUS, in the windows (shifts) zero, five, and ten. Given users' emotional scores, they were divided into six scales (in different colors), ranging from very depressed to very euphoric. These ranges were established based on the users' standard deviation, where there is a difference of at least 20% between them. On a scale of 0 to 1 (light green color), we define the users as happy for presenting positive feelings within the VADER range, which goes from -1 to 1. In the range of 1 to 2, we defined the user as euphoric (moss green), as he demonstrated much more positive feelings. From 2 (yellow) onward, we define the user with signs of euphoria because the community is among depressives. These users would be showing euphoria and joy far above the average than the environment suggests.

On the more negative side, users from 0 to -1 (bluish-green) were classified as sad ones, for showing negative feelings and expressions but still within the VADER standard. From -1 to -2 (dark green), users were classified as depressive, as they showed above-average negativity. From -3 on (blue), the users are defined as very depressives since they extrapolated the number of negative feelings.

Observing the User Score results showed in Figure 8, the growth rate in Figure 6 and the dynamic behavior of communities in Figure 7 using F-score, it is possible to note that there is an increased expression on negative emotions, an increase in community rate, and a height exchange of active users between communities in the same shifts.

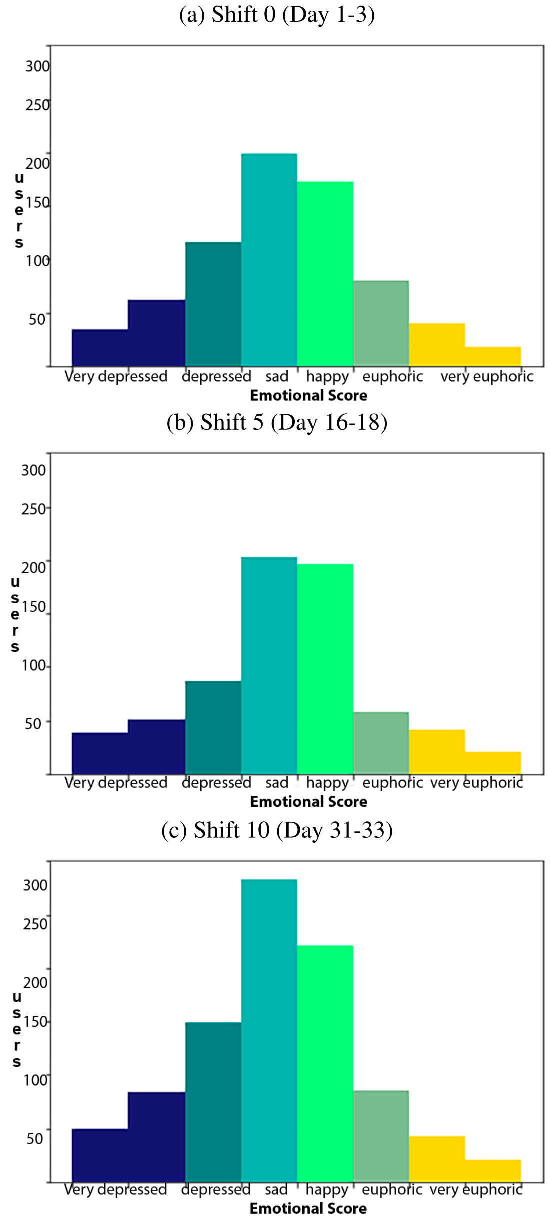

FIGURE 8. Histograms of the number of users classified according to their emotional score along time using EMUS.

IV. DISCUSSION

This study identified a high level of proximity patterns between depressive people who have similar behavior patterns. The most active users are grouped with their peers, and in less active users, the same effect is observed. Perhaps this proximity occurs because it is easier to approach and interact with people whose experience and similarly express themselves, creating greater intimacy.

A. TAKEOUTS FROM EXISTING WORKS

Our study corroborates with those of other studies [19], [50]. In [50]), the authors employed traditional instruments (CES-D on depression and IPIP NEO-Domain items on neuroticism questionnaires) to measure depression and neuroticism. The authors shared the questions of CES-D and IPIP NEO-Domain via a survey with social media users and compared with the number of posts and comments, *i.e.*, the user frequency activity using statistics (mean, median, frequency, standard deviation). The results demonstrate similar personality patterns among those whose group demonstrate that engagement in activities is related to the users' level of depression and how much-depressed users are inclined to do more broadcast. Likewise, Choudhury *et al.* [19] applied a survey on MKturk (https://www.mturk.com/) and used the lexicons ANEW and LIWC to extract categories from the text with the users' posts frequency. Unlike the works cited, our computational solution does not directly interact with users by interviews nor questionnaires. Our approach is automatic and combines different complex network metrics to extract emotional categories using EMUS. This automatic approach allows specialists to perform a premature analysis and recognition of depression indications, enabling timely interventions.

Despite the effectiveness in identifying behavioral patterns among depressed users of social networks, our study also pointed out that the social network may not be an adequate environment for developing coping strategies in this population. The observed effects depicted in Figure 8 show that the proximity between peers, due to similar characteristics, promoted an increase in negative feelings (sadness, depression), while positive feelings remained or decreased. This may be because the interaction does not happen between people who have different characteristics, which can hinder the development of learning new behaviors. Although social networks are beneficial to users' mental health, in [51] the authors identified that greater participation and the more significant number of friends on Facebook were related to less depressive symptoms. The way these relationships are established (types of groupings developed) may significantly impact behavior change. The present study also has raised other relevant questions. For example, if social networks can become an adequate environment for interaction and mental health promotion, would they be sufficient for this task? In [52] the authors found an increase in depressive symptoms among people who are highly active on social networks and reported having few or not having close friends outside of social networks (face to face). In contrast, people who reported a more significant number of close friends outside the network (face-to-face) indicated fewer depressive symptoms. The interactions established on social networks are useful for identifying patterns of behavior and predicting diagnoses of depression. However, as interactions naturally happen among people with related interests, such interactions do not seem to be useful (or even sufficient) to promote the reduction of depressive symptoms.

B. FINAL CONSIDERATIONS AND FUTURE WORK

In this work, we graphically and quantitatively discussed the temporal interaction of users in social media, focusing on emotions and depression. Our method allows specialists to follow the behavior of a community of interest, analyzing their interaction systematically. The analysis provided in this study also indicated a relationship between the pattern of interaction and emotional responses between users. The interaction is beneficial when there is a high degree of proximity between users when communities are dense and feelings are negative. What has been observed is that depressive users interact only with users who have the same degree of interactions and similar emotional characteristics. Although there are positive feelings, the interaction occurs better when there is a more significant negative feeling. This leads to the reflection that depressive users on social networks tend to get closer to other people who express negative feelings.

V. CONCLUSION

This paper presents an approach to investigate the interaction and emotional behavior among depressed users on social networks. Initially, we modeled users' interaction behavior using algorithms and metrics of complex networks, and we evaluated the structures with their intrinsic metrics. We also developed a method that combines two lexicons to extract emotional and contextual features from users' texts: posts and comments. A crawler was developed, and posts were collected from 1,212 users from a mutual support community about depression on Reddit. Part of the users was also evaluated by a survey with questions of PROMIS of depression level 2 for adults [23], which demonstrated that most of them have severe depression.

The results showed a high correlation between interaction and mixed emotional behaviors, varying between positive and negative feelings. However, the expression of negative feelings is much greater and more evident. Regarding the interactions, results suggest that networks are a suitable environment for mutual support when groups are dense and have a high similarity between them in terms of form, performance, and proximity of interactions.

The obtained results suggest that emotional aspects may be closely linked to how users interact and their profile, demonstrating that it is more effective and comfortable to obtain mutual support with friends (connections) closer in the distance and behavior. On the other hand, this draws attention to the difficulties that depressive users have in establishing relationships and engagement with different people, who comment or post about other subjects, demonstrate different emotional expressions and affection, and do not have a degree of similar interaction. In short, depressives prefer to communicate with equals.

In this study, we highlight the following contributions: (i) an approach that takes advantage of complex networks to assess the interaction and emotional behavior in social networks considering the temporal aspects of such interactions; (ii) a method for extracting emotional features and building an emotional user score based on the content of user's posts and comments; (iii) the discovery of ranges of features values that indicate mood disorders; (iv) a correlation analysis between the interaction patterns and the emotional aspects was highlighted in our modeling in the top communities.

By exploring technologies and general approaches to graphs, temporal analysis, and text-mining, our proposed approach is not limited to the context of data from depressive users on social networks. Therefore, it can be used for other graph-oriented databases that use text as the primary information. In this way, it is possible to explore other contexts and platforms that use texts, such as anxiety in chatbots. As future work, we encourage:

1) Comparing the behavioral patterns found in one community with the behavior of others;
2) Further exploring of the developed approach with other communities of mutual support regarding other diseases, transgender and contexts, such as anxiety, drug addictions, crimes, schizophrenia, among others; and
3) Adapting the approach to other graph-oriented database contexts, such as problem logging on mobile devices and collaboration of computer scientists behavior in code versioning systems.

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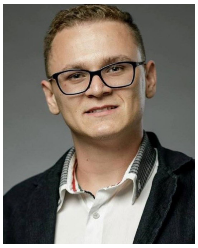

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