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Research Paper

Mapping emotional perceptions from stakeholders' survey using natural language processing in the management of chronic mental illnesses—perspectives from qualitative analytics

Abhishek Cukkemane [a,b,c,*], Veralia Gabriela Sanchez [d]

[a] Institute of Biological Information Processing, Structural Biochemistry (IBI 7), Forschungszentrum Jülich, Jülich, Germany
[b] Institut für Physikalische Biologie, Heinrich Heine University Düsseldorf, Düsseldorf, Germany
[c] Hanse-Wissenschaftskolleg Institute for Advanced Study, Delmenhorst, Germany
[d] Faculty of Technology, Natural Sciences and Maritime Sciences, University of South-Eastern Norway, Vestfold, Norway

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ABSTRACT

Chronic mental illnesses (CMI), such as schizophrenia, schizoaffective disorder, bipolar disorder (BD), and major depressive disorder (MDD), place a substantial burden on individuals, family, society and the healthcare infrastructure. Existing treatment methods fall short in addressing the needs of patients thereby leading to inadequate care and less-than-optimal health outcomes. To address this gap, our study explores a patient-centric approach through leveraging text mining and natural language processing (NLP) techniques by analysing transcribed interviews from various stakeholders, including clinicians, researchers, and healthcare professionals. Using, sentiment analysis, we examined and categorized the emotions and sentiments expressed in CMI-related discourse and explores the application possibilities using the four different lexicons in the syuzhet package in R to analyse open-ended responses in management of CMIs within academic, social and medical frameworks. The findings indicate that NRC lexicon provided text analysis methods with valuable insights into participants' emotional and attentional focus, thereby deepening our understanding of patient experiences and their reactions to interventions. Additionally, we compare sentiment analysis with outcomes from qualitative content analysis to evaluate their effectiveness in routine scientific applications and policy making. Integrating sentiment analysis into CMI management has the potential to enhance patient-centred care, ultimately leading to improved treatment outcomes. This research emphasizes the importance of leveraging innovative, data-driven methodologies to supplement conventional psychiatric care and policy development, fostering a more holistic comprehension of CMIs.

1. Introduction

Chronic mental illnesses (CMIs), such as schizophrenia, bipolar disorder (BD), and major depressive disorder (MDD), affect millions worldwide and present a significant burden on individuals, healthcare systems, and society (van Os and Kapur, 2009). Effective management of these disorders requires a multifaceted approach, involving healthcare professionals, policymakers, and social support systems. However, despite advancements in medical guidelines such as Diagnostic and Statistical Manual of Mental Disorders (DSM, 2013) and International Classification of Diseases (ICD, 2022), CMIs remain difficult to diagnose due to overlapping symptoms, leading to frequent misdiagnoses. For example, differentiating between various CMIs is often challenging (Smith and Craddock, 2011; van Os and Kapur, 2009), resulting in inappropriate treatment strategies that may hinder recovery. Although diagnostic accuracy has improved in recent decades (Paul and Potter, 2023), healthcare systems still struggle to provide holistic and patient-centred care because substantial gaps in care remain, with deviations from statutory guidelines contributing to poor treatment outcomes.

Given these limitations, there is a growing need for alternative methods to enhance psychiatric care. Understanding the diverse requirements of participants involved in psychiatric welfare is crucial. In a recent study, we conducted thematic qualitative analysis (Cukkemane et al., 2025) based on interviews with professionals, including clinical researchers, scientific researchers, pharmaceutical company managers,

* Corresponding author at: Institute of Biological Information Processing, Structural Biochemistry (IBI 7), Forschungszentrum Jülich, Jülich, Germany.
E-mail address: a.cukkemane@fz-juelich.de (A. Cukkemane).

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doctors, nurses, entrepreneurs, and social workers. The findings suggested a holistic, patient-centred management approach aligned with the biopsychosocial model (Engel, 1978, 1979) proposed by Dr. George Engel. Qualitative content analysis (QCA) (Anker-Hansen et al., 2020; Graneheim and Lundman, 2004; McCormack and McCance, 2006) and stakeholder interviews offer a microscopic view of psychiatric health welfare, capturing experiences, challenges, solutions, and daily activities that quantitative approaches often overlook. However, developing more reliable models and policies, one will require analysing a large number of interviews, a process that can be daunting when done manually in the traditional QCA. To address this challenge, we explored the potential of text mining (Arnold, 2017; Rutkowski et al., 2022; Yu, 2011) as a powerful tool in qualitative analytics. Text mining enables researchers to extract meaningful insights from large volumes of textual data. This strength of text mining analytics has found applications in politics (Hoffmann, 2018), social media analytics (Pv et al., 2024; Shehu et al., 2020), arts and humanities (Hoyeol, 2022) to name a few. Particularly in this case, sentiment analysis (Isasi, 2023; Yu, 2011) can computationally assess emotions expressed in stakeholder opinions in management of CMIs. This technique offers deeper insights into patient experiences, emotional states, and unmet needs in mental health care, ultimately enhancing psychiatric welfare through data-driven decision-making.

Herein, we employed sentiment analysis using the NRC Emotion Lexicon, a comprehensive tool developed by the National Research Council Canada (Mohammad and Turney, 2013). Unlike other lexicons, NRC categorizes words not only into positive or negative sentiment but also into eight basic emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. With over 14,000 annotated words, it allows for a nuanced understanding of emotional expression in text. The lexicon is popular among several literary scholars because it is available in over 100 languages, making it accessible for cross-cultural research. By applying NRC-based sentiment analysis to open-ended responses from key participants including clinicians, researchers, social workers, and patients. We aim to identify critical gaps in current CMI management approaches (Moren, 2024; Moreno-Poyato et al., 2021; Wiegand et al., 2020) that include diagnosis, treatment, patient welfare among others, and compare these findings to the outcomes of our previously reported qualitative content analysis (Cukkemane et al., 2025).

This study highlights the importance of integrating qualitative sentiment analysis into psychiatric care to complement traditional diagnostic and treatment methods. By capturing emotional and attentional focus in textual data, sentiment analysis can help refine treatment plans, improve patient communication, and guide policy changes. Our findings align with Engel's biopsychosocial model, emphasizing the interconnectedness of biological, psychological, and social factors in mental health care. This research provides experimental evidence supporting a comprehensive, patient-centric approach to CMI management, offering a novel framework for improving psychiatric care through data-driven methodologies.

2. Methodology

2.1. Aim and research question

This study investigates whether text analysis of interview transcripts, particularly sentiment analysis, can provide valuable insights into patient needs. Such insights may help guide more effective patient-centred mental health interventions for the management of CMIs such as schizophrenia, BD, and MDD.

2.2. Ethical considerations

In accordance with Article 5(1)(d) (ac curacy) and Article 5(1)(f) (integrity and confidentiality), as well as Article 32 (security) of the General Data Protection Regulation (GDPR), informed consent was obtained from all participants and the data was anonymized. The study was notified with the Data Protection Services of Sikt – Norwegian Agency for Shared Services in Education and Research (reference number: 648482). The legal basis for data processing was established under GDPR Article 6(1)(a), ensuring compliance with ethical and data protection standards.

2.3. Participant recruitment

As described in reference (Cukkemane et al., 2025), we recruited individuals engaged in the management, support, and care of schizophrenia and related chronic mental illnesses (CMIs). Eligibility criteria included individuals engaged in the management, support, or care of schizophrenia and related complex mental illnesses (CMIs), including caregivers and healthcare professionals such as psychiatrists, researchers, social workers, and nurses. Also, because of the high global prevalence of CMIs (3–5 %), few participants provided perspectives not only in their professional capacity but also from personal experience, due to having close family members affected by chronic mental illnesses by CMIs. The professional participants included caregivers, psychiatrists, researchers, social workers, and nurses. Briefly, participants were identified through multiple strategies, such as convenience sampling via the authors' professional network, email-invited experts based on their scientific and snowball sampling, where existing contacts recommended other potential participants. A total of 57 individuals (23 females and 34 males) from Germany, the UK, Norway, and Denmark were initially contacted through various recruitment strategies, including email outreach and professional networking, to represent diverse healthcare systems across Europe. Of these, 7 (see Table 1) participants ultimately consented and completed the in-depth interviews, while the remaining 50 either did not respond, declined participation, or were unavailable during the interview period. Given the small sample size, limited participant diversity, and the European focus of participants, the findings may lack representativeness and carry potential bias, particularly due to the absence of perspectives from patients, families, and medical professionals. The participants were interviewed through semi-structured interviews as reported in (Cukkemane et al., 2025). The length of the interviews averaged between 35–50 min and the interviews were transcribed verbatim, which serves as data source for this work.

2.4. Data analysis

To explore the emotional undertones embedded in the interview data, sentiment analysis was employed using the syuzhet package in R (Jockers, 2020; Naldi, 2019) that includes lexicons such as syuzhet (Jockers, 2020), NRC Emotion Lexicon (Mohammad and Turney, 2013), afinn (Nielsen, 2011), and bing (Bing, 2012). We first tested all the lexicons for the dispersity of the scores across the spectrum of positive to negative sentiments. Examination of emotional patterns and the ten most prominent words from the stakeholder narratives provides us with a variety of categorical variables, i.e., the central codes that can be compared with themes from qualitative analytics (Cukkemane et al., 2025).

The sentiment analysis workflow involved the following steps: loading the syuzhet package, tokenization of sentences and words from the recorded interview transcripts. This was followed by extraction of sentences using the NRC Emotion Lexicon, emotional and sentiment-related data were extracted from the textual responses. The extracted data were visualized and summarized using tables, bar charts, word clouds, and trajectory plots. The trajectory plot describes normalized sentiment values across time for the participants and can roughly be divided into three key frameworks as described in the questionnaire (Cukkemane et al., 2025), i.e., “tasks related to diagnosis”, “challenges with current procedures”, and “expectations from newer diagnostic methods”. These visualizations illustrate the distribution of sentiment and emotional categories across the participant's narratives. The

Table 1
Summary of sentiment analysis across professional stakeholders (*Participants with friends and family members affected by CMIs).

	Positive	Negative	Neutral
P1 (Sex = Male; Education = MD, Ph.D; Specialization = Psychiatry; Current Role = Scientist; Previous Role = Clinician; Experience (in year) > 20)			
NRC	0.274648	−0.08451	0.640845
afinn	0.053883	−0.02324	0.922874
Bing	0.029054	−0.01321	0.957739
syuzhet	0.039937	−0.01442	0.945642
P2* (Sex = Male; Education = MD, Ph.D; Specialization = Neurosciences; Current Role = Scientist; Previous Role = Clinician; Experience (in year) > 15)			
NRC	0.263576	−0.09801	0.638411
afinn	0.096886	−0.0346	0.868512
bing	0.052595	−0.01765	0.929758
syuzhet	0.042353	−0.01952	0.938131
P3* (Sex = Male; Education = Ph.D, MBA; Specialization = Biochemistry; Current Role = CEO - Entrepreneurship; Previous Role = Scientist; Experience (in year) > 15)			
NRC	0.229752	−0.12397	0.646281
afinn	0.077807	−0.03808	0.88411
bing	0.041366	−0.02397	0.934668
syuzhet	0.037886	−0.01814	0.943976
P4 (Sex = Male; Education = Ph.D; Specialization = Medicinal Chemistry; Current Role = COO - Entrepreneurship; Previous Role = Scientist; Experience (in year) > 10)			
NRC	0.287719	−0.07485	0.637427
afinn	0.064182	−0.01851	0.917304
bing	0.034806	−0.01333	0.951864
syuzhet	0.044495	−0.00823	0.947272
P5 (Sex = Male; Education = Ph.D; Specialization = Psychiatry; Current Role = MD Pharamaceuticals; Previous Role = Scientist; Experience (in year) > 20)			
NRC	0.215479	−0.12401	0.66051
afinn	0.051554	−0.0404	0.908044
bing	0.027239	−0.0192	0.953565
syuzhet	0.030146	−0.02042	0.949433
P6* (Sex = Female; Education = MS; Specialization = Informatics; Current Role = CEO -Social entrepreneurship; Previous Role = IT specialist; Experience (in year) > 3)			
NRC	0.24237	−0.10413	0.653501
afinn	0.064504	−0.02212	0.91338
bing	0.039071	−0.01511	0.945816
syuzhet	0.040509	−0.01426	0.945227
P7 (Sex = Male; Education = BSN; Specialization = Nursing; Current Role = Nurse; Previous Role = None; Experience (in year) < 1)			
NRC	0.237288	−0.13877	0.623941
afinn	0.101779	−0.03874	0.859486
bing	0.053755	−0.0249	0.921344
syuzhet	0.042401	−0.0218	0.9358

R-scripts employed for all the analysis with the different lexicons have been provided in the supplementary section along with the detailed breakup of sentiments in comma-separated files for every participant.

3. Results

3.1. Sentiment variations across different lexicons

The sentiment analysis results for seven participants (Table 1) with diverse professional backgrounds reveal notable trends in emotional expression across their transcripts. Overall, the analysis reveals that participants primarily use neutral language, with positive sentiment generally outweighing negative sentiment, with proportions ranging from 62.3 % to 96 %, indicating that either the majority of the language used in their transcripts or the lexicons themselves are biased to emotionally neutral tones. Positive sentiment varies between 2.7 % and 28.7 %, with P4 displaying the highest positivity, while P3 and P5 show lower positive sentiment scores. Negative sentiment is generally low, ranging from 0.8 % to 13.9 %, with P7 exhibiting the highest negativity, possibly reflecting early career stress or challenges.

Among the sentiment analysis methods, NRC consistently assigns higher positive sentiment than the other methods, often exceeding 20 %. At the same time, it also assigns a notable amount of negative sentiment but not as much as the positive scores thereby providing a wider range of sentiments from positive and negative scores. Afinn's sentiment scores tend to show fewer extremes in values for both positive and negative sentiments but leans towards neutral sentiment. The difference between positive and negative scores is however smaller than NRC. Bing and Syuzhet show the lowest negative sentiment scores, suggesting they are far more conservative and seem more neutral-heavy.

As NRC based analytics distribute sentiment more widely, we believe it is better suited for qualitative analytics. In addition, the data is also suggestive of variations in sentiment reflecting across professional roles, with entrepreneurial and scientific roles generally showing higher positivity, while clinical and early-career roles exhibit slightly higher negative sentiment.

3.2. Emotions across stakeholders

Emotional analysis of Participant 1′s discourse (Fig. 1**, P1**) revealed trust (20 %) as the dominant emotion, followed by anticipation (16 %) and fear (14 %). The prominence of trust aligns with this participant's extensive clinical background (>20 years) and medical training. Anger (12 %) ranked higher than in most other participants, potentially reflecting frustration with system limitations encountered during clinical practice.

Analysis from the word cloud (Fig. 1**, P1**) highlighted "money", "kind", "disease", "diagnosis", "good", "medical", "interested", "treat", "feeling", and "patient" as ten most prominent words in this participant's discourse. These words can broadly reflect themes "medical diagnosis and treatment", "financial concerns", "healthcare", and "emotional well-being". The sentiment valence trajectory (Fig. 3, **P1**) demonstrated significant fluctuations, with notable dips when discussing diagnostic challenges and healthcare system fragmentation. Peaks occurred during discussions of evidence-based treatments and potential system improvements. The trajectory showed an overall slight positive trend, suggesting cautious optimism despite acknowledged limitations.

Participant 2′s emotional profile showed the highest levels of trust (22 %) among all participants, followed by anticipation (15 %) and fear (13 %). This participant also expressed higher levels of sadness (11 %) compared to most others (Fig. 1**, P2**). The word cloud emphasized "disease", "patient", "success", "suffering", "problem", "tumour", "friendship", "truth", "communication", and "management" as the prominent words and the sentiment valence trajectory (Fig. 3, **P2**) showed stability in the positive range when discussing research advances and evidence-based approaches, with dips when addressing implementation barriers and research-to-practice gaps. The trajectory demonstrated a pronounced positive surge when discussing integrated and possibilities of newer diagnostics approaches, corresponding with this participant's emphasis on holistic research frameworks. Altogether, the suggestive central themes fall into "medical diagnosis and treatment", "healthcare management", "emotional well-being, "communication and support", "problem solving and achievement".

Emotional analysis of Participant 3 (Fig. 1, **P3**) revealed anticipation (18 %) as Participant 3′s dominant emotion, closely followed by trust (16 %) and fear (15 %). This participant showed higher levels of joy (10 %) than most others, reflecting an entrepreneurial optimism about innovation potential in CMI management. The word cloud (Fig. 1, **P3**) highlighted "medical", "patient", "disease"; "cancer"; "problem"; "schizophrenia"; "suffering"; "depression"; "career", and "reward" with central themes being "health and illness", "emotional well-being and support", "problem solving and achievement". This was reflected in the sentiment valence trajectory (Fig. 3, **P3**) showed an overall positive trend with significant peaks when discussing technological solutions and innovation opportunities. Negative valleys appeared when addressing regulatory barriers and implementation challenges. The trajectory demonstrated the most pronounced positive-negative oscillations among all participants, potentially reflecting the tension between entrepreneurial optimism and recognition of practical constraints.

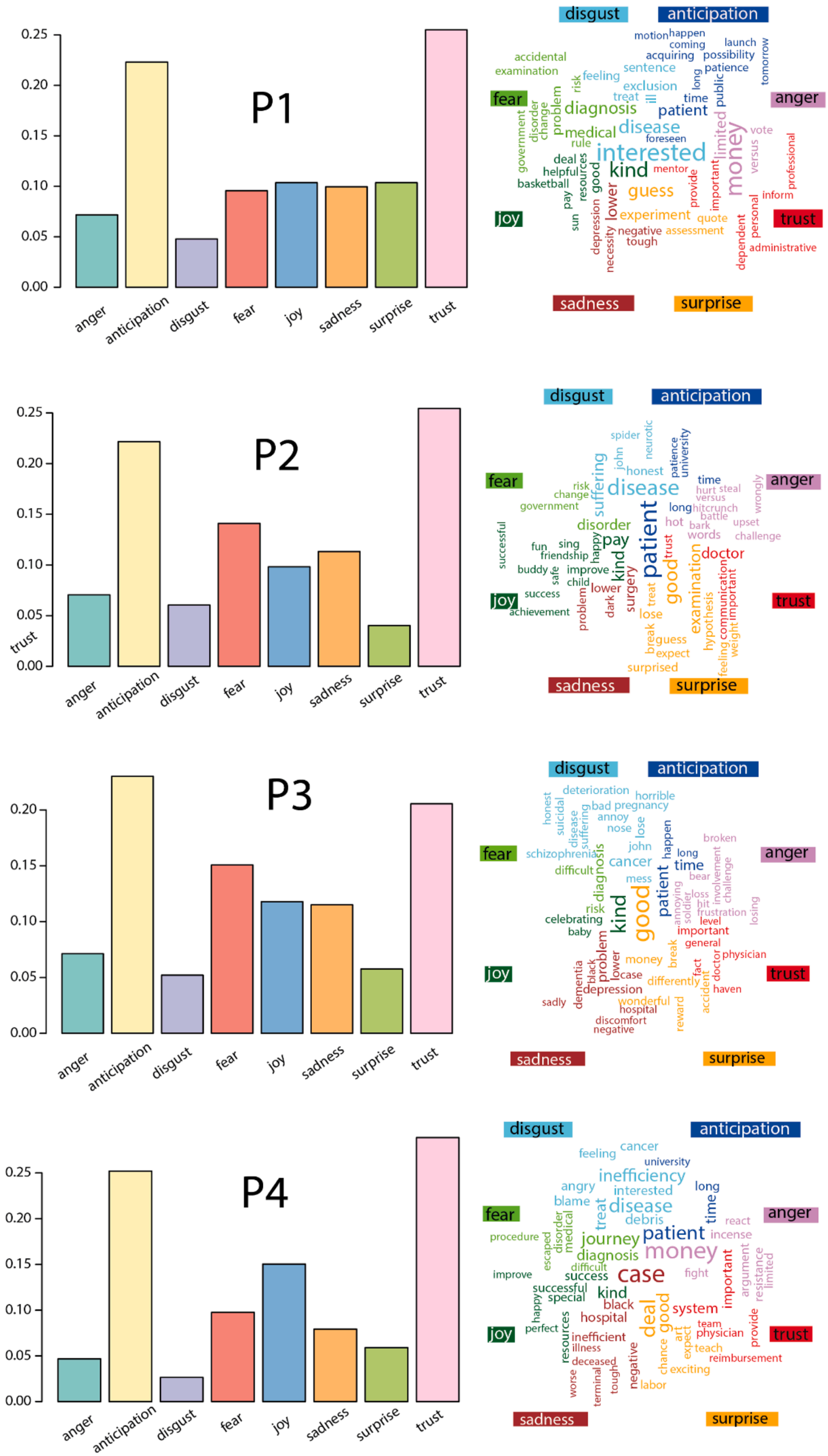

Fig. 1. Bar chart showing the calculated scores of the eight emotions from the NRC lexicon and word cloud for participants 1–4 of the most frequent words corresponding to the same emotion set.

Participant 4 displayed the lowest positive sentiment (3.0 %) among all participants while maintaining similar negative sentiment levels to others. The emotional analysis revealed trust (18 %) as dominant, followed by fear (16 %) and anticipation (14 %) as highlighted by predominant words (Fig. 1, **P4**) in the cloud “medical”, “patient”, “success”, “disease”, “cancer”, “resources”, “happy”, “prognostic”, “treat”, and “risk" reflecting central themes such as “health and illness”, “treatment and care”, “resources and support”, “problem solving and achievement”. The sentiment valence trajectory showed the most pronounced negative trends when discussing regulatory challenges and trial limitations for psychiatric medications Peaks corresponded with discussions of new measurement approaches and potential breakthroughs in targeted treatments. The overall trajectory (Fig. 3, **P4**) demonstrated more negative segments than most other participants, potentially reflecting industry-specific challenges in psychiatric drug development. This participant showed the highest levels of disgust (10 %) among all participants, potentially reflecting frustration with pharmaceutical industry constraints.

Participant 5 demonstrated a high degree of positive sentiments with emotional analysis (Fig. 2, **P5**) showing anticipation (17 %) and trust (17 %) as dominant factors, followed by joy (11 %) and fear (12 %). This emotional profile aligns with an innovation-focused perspective grounded in scientific training as emphasized in the word cloud (Fig. 2, **P5**) comprising of “disease”, “patient”, “cancer”, “medical”, “suffering”, “treat”, “schizophrenia”, “risk”, “happy”, and “problem". The sentiment valence trajectory (Fig. 3, **P5**) maintained a consistent positive trend, with minimal negative excursions compared to other participants. The most significant peaks occurred during discussions of precision medicine approaches and biomarker development, while slight dips accompanied discussions of regulatory challenges and development timelines

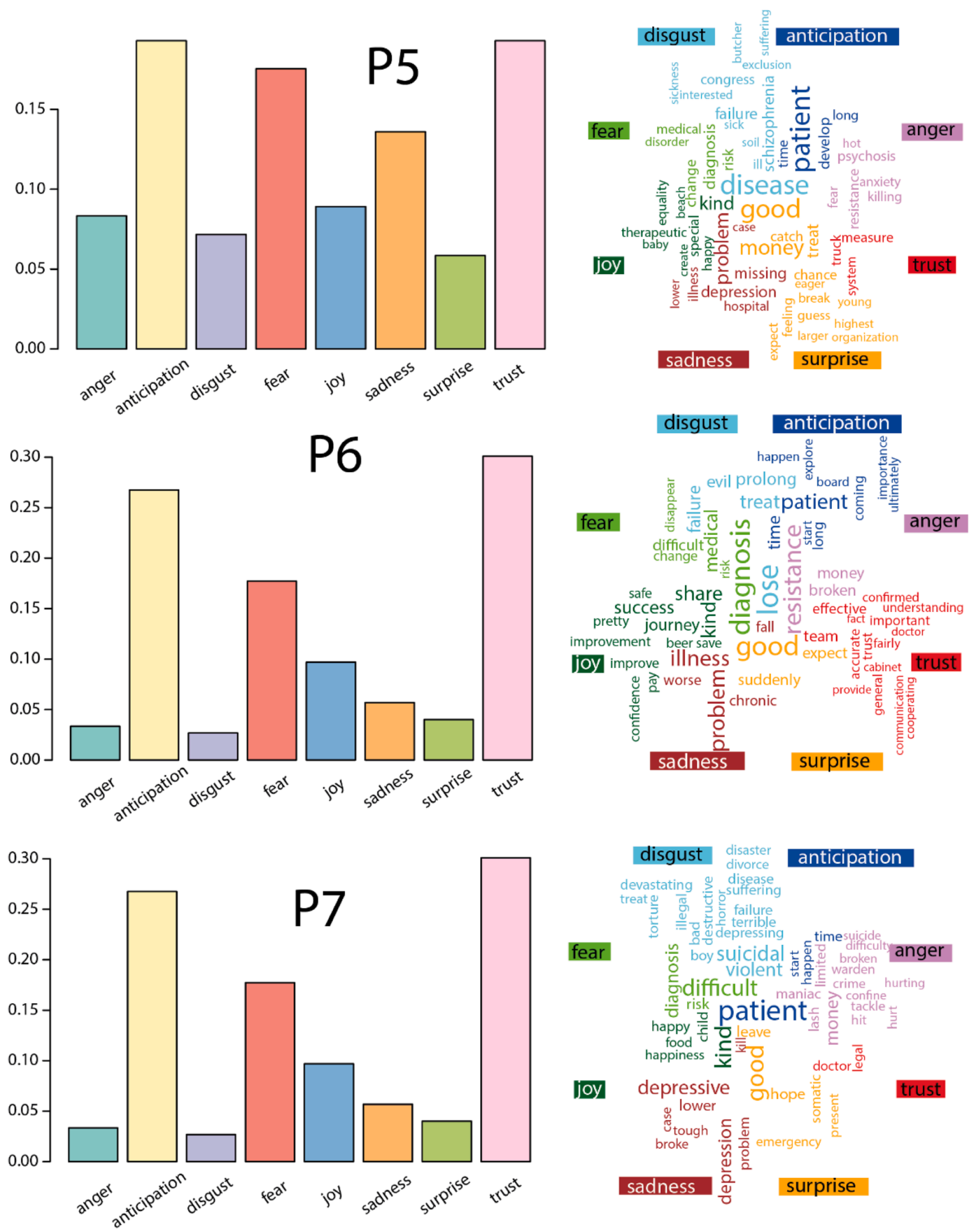

Fig. 2. Bar chart displaying the computed scores of eight emotions from the NRC lexicon, alongside a word cloud for participants 5–7 highlighting the most frequently used words associated with these emotions.

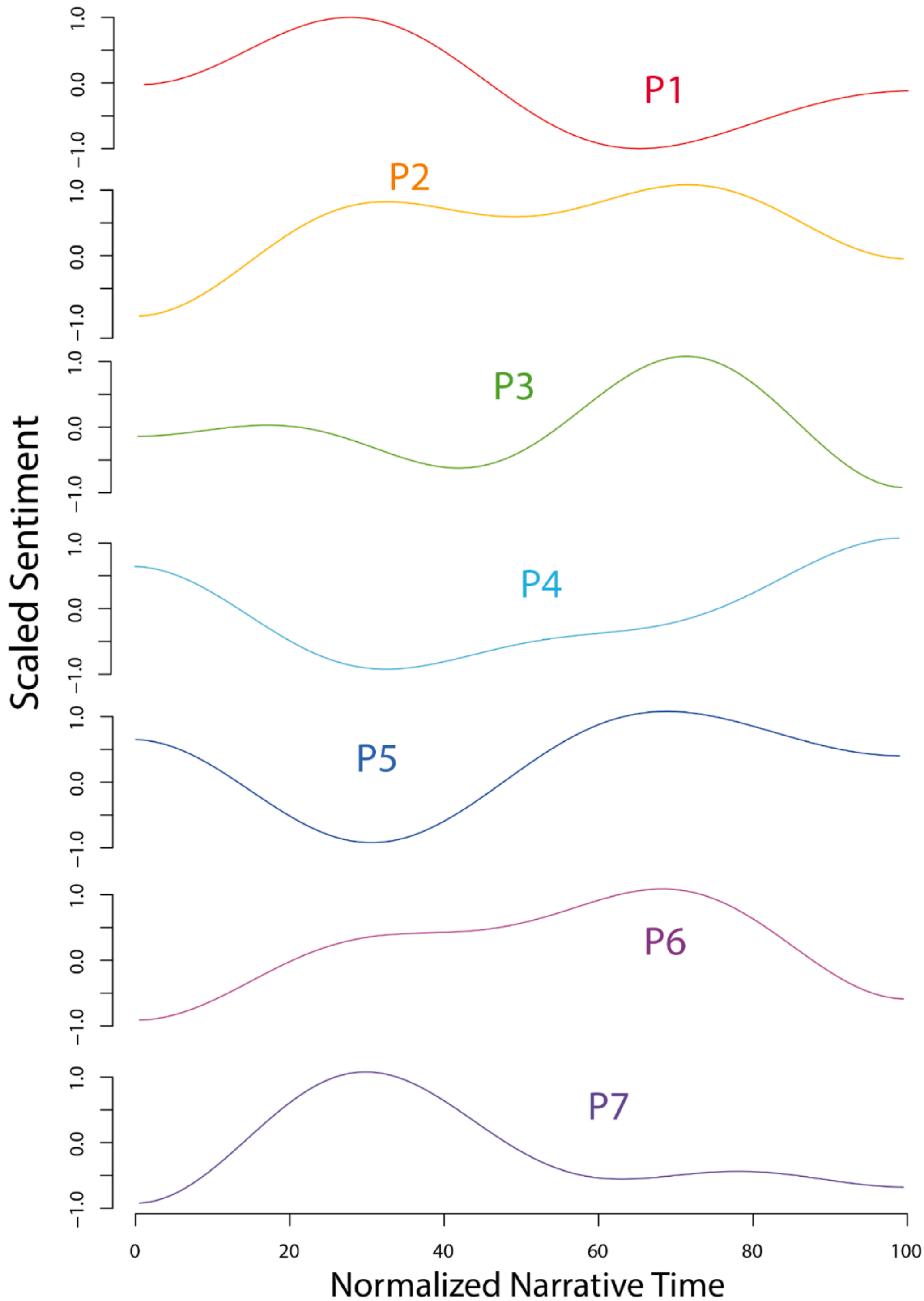

Fig. 3. Evolution of sentiments the during the course of the interview for the seven participants, which was scored on the basis of the NRC lexicon. Y-axis shows positive (1.0), neutral (0.0) and negative (−1.0). The x-axis shows the elapsed time of the narrative.

reflecting expertise in pharmaceutical approaches to mental health. The narrative emphasized themes central to “treatment and care”, “emotional well-being”, “risk management”, and “healthcare”.

Participant 6 demonstrated a completely different emotional profile (Fig. 2, **P6**) with higher levels of sadness (12 %) and disgust (11 %) than other participants, while still maintaining trust (15 %) and anticipation (15 %) as dominant emotions. The word cloud (Fig. 2, **P6**) emphasized “patient”, “medical”, “diagnosis”, “success”, “treat”, “risk”, “time”, “problem”, “illness”, and “improve”, highlighting themes in “communication and support”, “problem solving and improvement”, “treatment and care”, and “time and risk management”. This pattern likely reflects direct experience with the human impact of system limitations as both a social worker and family member of someone with CMI greatly reflecting the focus on practical challenges faced by individuals and families navigating mental healthcare systems. The sentiment valence trajectory (Fig. 3, **P6**) showed significant negative excursions when discussing system navigation challenges and caregiver burden. Peaks appeared during discussions of community support and advocacy efforts. The trajectory demonstrated rapid oscillations between positive and negative sentiment, potentially reflecting the complex emotional reality of supporting individuals with CMIs through fragmented systems.

As the participant with the least professional experience (>1 year), Participant 7 showed a distinctive emotional profile (Fig. 2, **P7**) with higher levels of surprise (11 %) than other participants, alongside trust (18 %), anticipation (16 %), and fear (15 %). The predominant words (Fig. 2, **P7**) in the cloud highlighted “patient”, “success”, “diagnosis”, “happiness”, “disease”, “time”, “suffering”, “problem”, “trust”, and “resources" reflecting front-line clinical nursing perspectives. The sentiment valence trajectory (Fig. 3, **P7**) showed consistent fluctuations with dips corresponding to discussions of staffing challenges and care coordination issues. Peaks occurred when discussing direct patient care and therapeutic relationships aligning with central themes as “support and relationship”, “emotional well-being”, “time management”, and “problem solving and achievement”. The trajectory demonstrated an overall neutral trend with balanced positive and negative segments, reflecting the practical, day-to-day reality of psychiatric nursing practice.

3.3. *Dominant emotions and trajectories across stakeholders*

Trust emerged as the most prevalent emotion (Figs. 1 and 2) across all stakeholder roles, comprising 15–22 % of the emotional content. This finding suggests that despite challenges in CMI management, participants maintain confidence in certain aspects of care systems or professional relationships. Following trust, anticipation (14–18 %) and fear (12–16 %) were the next most prominent emotions, reflecting the tension between hopeful expectations for improved care and concerns about current limitations.

Among healthcare professionals (Participants 1, 2, 5, and 7), trust and anticipation were particularly pronounced, suggesting their professional training may in still greater confidence in established protocols despite recognizing limitations. For participants with personal experiences with CMIs (Participants 2, 3, and 6), fear and sadness showed higher prominence compared to other participants, potentially reflecting the emotional toll of witnessing loved ones navigate complex healthcare systems.

Clinicians (Participants 1, 2, and 5) demonstrated higher levels of trust (18–22 %) compared to non-clinical professionals (15–17 %), possibly indicating greater faith in medical approaches. However, they also expressed more anger (10–12 %) than other groups (7–9 %), suggesting frustration with systemic barriers to optimal care.

Entrepreneurs with scientific backgrounds (Participants 3 and 4) showed the highest levels of anticipation (17–18 %) and joy (9–10 %), potentially reflecting their solution-oriented perspectives and investment in innovative approaches to mental healthcare. The social worker (Participant 6) demonstrated the highest levels of disgust (11 %) and sadness (12 %), perhaps reflecting direct exposure to the human consequences of healthcare system failures.

The nurse (Participant 7), with the least professional experience among participants, showed the highest level of surprise (11 %), possibly indicating gaps between theoretical training and clinical realities in CMI management.

Fig. 3 illustrates the emotional trajectories across interview narratives, revealing dynamic shifts in emotional tone as discussions progressed through different topics. For all participants, discussions related to current diagnostic procedures and challenges triggered increases in negative emotions (fear, anger, and sadness), while conversations about potential improvements and future directions stimulated positive emotions (trust, anticipation, and joy).

4. Discussion

Working with qualitative research methods (Anker-Hansen et al., 2020; Graneheim and Lundman, 2004; McCormack and McCance, 2006)) is a challenging affair as they often require manual analysis that is processed iteratively, and is hence time-consuming. Due to this, data analytics is rather restricted to a handful of samples. We were curious to comprehend whether text mining-based approaches and sentiment analysis (Arnold, 2017; Rutkowski et al., 2022; Yu et al., 2011) can support large-scale qualitative data analysis. This will help identify hurdles faced by patients and professional participants in management of CMIs from a patient-centric perspective. Therefore, we are testing the utility of different lexicons, and then using the best performing lexicon to compare with QCA results published previously.

4.1. *Comparative analysis across sentiment lexicons*

As outlined earlier, we compared sentiment analysis outcomes across different lexicons to evaluate their range and distribution in analysing sentiments related to CMI discourse. Among these, NRC (Mohammad and Turney, 2013) consistently assigned higher positive sentiment scores exceeding 20 % in few instances. At the same time, it also captured a notable amount of negative sentiment, though less than the positive. This indicates NRC’s ability to categorize emotion into eight discrete types (e.g., trust, fear, anticipation) allows for a more nuanced classification than a simple positive/negative scale. In contrast, Afinn’s (Nielsen, 2011) outputs were less dispersed with both positive and negative sentiments and leaned towards neutrality. The other two lexicons, Bing (Bing, 2012) and Syuzhet (Jockers, 2020), appeared less sensitive to sentiment variations and predominantly produced neutral scores.

Our findings of low negative sentiment scores agree with previous findings (Naldi, 2019), although the lexicons containing more negative than positive words. This discrepancy may be attributed to the Syuzhet package’s limitations in accounting for negators (Hoyeol, 2022; Naldi, 2019) thereby leading to significant differences in sentiment scores across various lexicons alike our observation (Table 1). Thus, the choice of sentiment analysis packages should be made carefully, depending on the specific requirements of the discipline. In our case, as we seek to understand the emotional responses of professionals managing CMIs, it was essential to capture a wide range of emotions. NRC’s broader sentiment distribution made it particularly well-suited for our qualitative analysis. Additionally, the data revealed variations in sentiment across professional roles: entrepreneurial and scientific roles exhibited higher positivity, while clinical and early-career roles reflected slightly higher negativity. As shown in Fig. 1 and 2, the distribution of words categorized into various emotions across professional groups provides a nuanced understanding beyond mere positive, negative, and neutral scores.

4.2. *Qualitative analytics through sentiment analytics*

In a previous report from our team (Cukkemane et al., 2025), we conducted qualitative analytics with data obtained from interviews using a semi-structured questionnaire that had three parts in it viz. “tasks related to diagnosis”, “challenges with current procedures”, and “expectations on newer diagnostics”. Such a framework was necessary to investigate the multi-dimensional challenges that the participants face on a day-to-day routine in management of CMIs.

4.3. *Tasks related to diagnosis*

In the early part of the narratives (Fig. 3) from the trajectory plot, participants P3, and P6 exhibit negative sentiments, likely reflecting frustration, dissatisfaction, or challenges related to the diagnostic tasks. This could stem from procedural inefficiencies, delays, or inaccuracies often associated with the diagnosis of chronic mental illnesses (CMIs). In contrast, P1 demonstrated positive sentiment during this phase, possibly indicating satisfaction or optimism regarding their experiences with diagnostic procedures. The remaining participants displayed a divergent set of emotions suggests that participants had differing levels of exposure to diagnostic systems or varying perspectives based on individual circumstances.

4.4. Challenges with current procedures

In the middle phase of the trajectory plot (Fig. 3), the narratives included responses for questions concerning challenges procedures, there is a significant fluctuation in negative sentiment scores. Participants such as P3, P4, and P5 show pronounced negative sentiment, highlighting dissatisfaction with the limitations or inefficiencies of existing procedures in managing CMIs. This could include issues such as lack of accuracy, accessibility, reimbursements or patient-centred care in the current systems. Notably, P3 and P4, both of who are in the entrepreneurial space appears to experience tonically negative sentiment, suggesting the deep dissatisfaction during this phase. This corroborates strongly with call of lack of infrastructure and development in the innovative space as highlighted in the Draghi report on EU competitiveness (Draghi, 2024). By contrast, the narrative from the remaining participants illustrates that these participants while not completely satisfied with the healthcare system perceive fewer challenges and/ or have adapted to the current systems regardless. Their perspectives may reflect experience, optimism or resilience in navigating the procedural difficulties.

4.5. Expectations from newer diagnostic methods

In the final phase of the trajectory plot (Fig. 3), which focused on narrations that described the expectations from newer diagnostic methods. At this end, there is a noticeable shift toward positivity for all participants but P1, which show a significant increase in positive sentiment, suggesting optimism, or enthusiasm for advancements in diagnostic tools and approaches. This phase may reflect participants' belief in the potential for newer methods to address the shortcomings of current systems and improve the management of CMIs.

However, not all participants experience a positive shift. P3 and P6 exhibit lingering negative sentiments toward the end of the narrative. This could reflect scepticism about the feasibility or effectiveness of newer diagnostic methods, or perhaps a lack of trust in their ability to resolve the challenges highlighted earlier in the narrative. These outliers illustrate that while many participants are optimistic about future developments, some remain cautious or unconvinced.

Qualitative Analytics – Biopsychosocial model *

Biological / medical factors	Social / societal factors	Psychological / psychosocial factors
1. Guidelines	1. Legality and bureaucracy	1. Disabled for life
2. Questionnaires	2. Diverse roles in profession	2. Lack of trust
3. Complexity in diagnosis	3 Pricing should not be a factor	3. Trust
4. Complexity in treatment	4. Ineffective medical support	4. quality-of-life
5. Lack of standardization	5. Right of treatment	5. patient journey
6. Resource management	6. Medical support	6. Emotional care
7. Combination diagnosis	7. Reimbursements	7. Vulnerability
8. Combination therapy	8. Time-effort	8. Patient centric
9. Technological requirements		9. Effort

Emotion and Sentiment Analysis

Biological / medical factors	Social / societal factors	Psychological / psychosocial factors
1. Medical diagnosis and treatment	1. Financial concerns	1. Emotional well-being
2. Healthcare	2. Healthcare management	2. Support and relationship
3. Health and illness	3. Communication and support	
4. Treatment and care	4. Problem solving and achievement	
5. Resources and support	5. Time and risk management	
	6. Problem solving and improvement	

Fig. 4. Comparison of themes derived from expert-based qualitative analytics (Cukkemane et al., 2025) versus sentiment analytics. The overlapping of themes is evident in both the qualitative analysis (above) and the NLP sentiment analysis (below).

4.6. Qualitative analytics vs sentiment analysis

One of the main objectives of this study is to assess the feasibility of applying text mining techniques to qualitative content analysis. Previous research (Isasi, 2023; Yu, 2011) suggests that text mining and qualitative methods are epistemologically similar, as both share methodological foundations in content analysis, particularly in terms of reliability and validation. Traditional qualitative approaches often rely on labour-intensive, iterative manual analysis, making it challenging to process large text-based datasets. Therefore, text mining provides an interesting alternative, enabling the extraction of meaningful patterns and insights. So, we were curious to validate whether the sentiment analysis conducted in this study is congruent with findings from a prior report on the same dataset.

Firstly, results obtained from qualitative analytics described approximately 30 different themes in patient-centred management approaches that aligns with George Engel's biopsychosocial model (Engel, 1978, 1979) encompassing biological, psychological, and social dimensions. In comparison, key themes that emerged from the sentiment analysis were fewer. We attribute this lower frequency in themes to the limited association with tokenization of negators and overall negative text in the sentiment analysis. However, when comparing the obtained themes (Fig. 4), for instance, among the biological /medical factors, we observed "combination diagnosis", "combination therapy", “complexity in diagnosis”, “complexity in treatment”, “technological requirements” that were previously reported; herein we noticed parallels in themes “medical diagnosis”, treatment and care”, and “health and illness”. In a similar vein, when comparing social/ societal factors, we observe similarities in management and money-matters such as “legality and bureaucracy”, “medical support”, “time-effort”, “reimbursements”,” pricing should not be a factor” in QCA against “time and risk management”, “financial concerns” and “healthcare management”. The emphasis on patient-centred elements appears prominently in both. For instance, we observed themes like "quality-of-life," "patient journey," "emotional care," and "vulnerability" under psychological factors in QCA, which directly corresponds to the “emotional well-being” and “relationship and support” emerges as crucial findings from the interviews.

The challenges related to healthcare system navigation are consistently and reliably identified using sentiment analysis.

4.7. Strengths and limitations

The application of sentiment analysis to CMI stakeholder interviews demonstrated several notable strengths. First, the methodology provided a systematic framework for detailing emotional dimensions of qualitative data, enabling more objective comparison across participants and topics. The nuanced approach reveals complexities that otherwise might be missed by traditional content analysis alone, for instance, in this case, we noticed the recurrence of the word “cancer” and “tumour”. In fact, among chronic diseases and medical care, cancer serves as the gold standard in healthcare practice that integrates multidisciplinary approaches combining specialized diagnostics, personalized treatment protocols, and comprehensive patient support systems. Other chronic illnesses, such as schizophrenia, BD and MDD, will benefit substantially from adopting similar comprehensive frameworks.

Secondly, sentiment analysis identified emotional patterns across professional backgrounds and experience levels, highlighting how different stakeholder positions influence perspectives on CMI management. While our sample spans four countries (Germany, UK, Norway, and Denmark), we acknowledge that the findings are not intended to be representative of any specific national healthcare system. These insights can inform more targeted approaches to stakeholder engagement and system improvement. For instance, during the upgrade of DSM IV to DSM 5 (Administration, 2016; Bredstrom, 2019) views of social sciences researchers in context to societal and cultural references were incorporated in diagnostic guidelines.

Third, the longitudinal emotional trajectory analysis revealed dynamic shifts in emotional tone as discussions progressed through different topics, providing context for understanding how various aspects of CMI management elicit. This temporal dimension offers valuable insights for structuring interventions and communications in ways that acknowledge and address emotional concerns.

Although, there are several positive factors, sentiment analysis has few shortcomings that needs to be considered. First, sentiment analysis relies on pre-defined lexicons with a finite number of words that have been factorized. Hence, then analysis may not fully capture the contextual nuances of specialized healthcare discourse. Negative words are not properly represented and technical terms common in professional practices may carry emotional connotations that vary from day-to-day language, potentially skewing analysis results.

Second, our small sample size ($n = 7$) limits the generalizability of findings, particularly given the European focus of participants. Professional demographics may skew toward certain specialties or experience levels, overlooking perspectives from other key stakeholders like patients, families, or policymakers. The analysis emphasizes emotional patterns without fully contextualizing structural factors that might drive these responses differently across healthcare systems with varying resources, training protocols, and cultural attitudes toward mental health. Moreover, the relative absence of patient voices limits understanding how recipient experiences align with or diverge from provider perspectives, a critical consideration for developing truly responsive care models that address the needs of those most directly affected by CMI management approaches. Furthermore, as noted in our methodology, the absence of certain professional perspectives (practicing physicians, social scientists in mental health, health insurance specialists, and policy makers) creates potential gaps in our understanding of the emotional landscape surrounding CMI management.

Third, sentiment analysis captures linguistic expressions of emotion but cannot access unexpressed feelings or nonverbal cues that might provide deeper insight into stakeholder perspectives. The methodology also assumes that emotional content in text reflects genuine emotional states, which may not always be accurate, particularly in professional discourse where emotional expression may be modulated by professional norms. In this work we have used NRC Sentiment and Emotion Lexicons, afinn and bing, and obtained good results with NRC. Other methods involving deep learning-based sentiment models were not considered due to the dataset size and computer resources. Nevertheless, future work can include data augmentation and training with deep learning-based sentiment models (Rasool et al., 2025), and compare the results with those reported in this article.

5. Conclusion and perspectives

Sentiment analysis of stakeholder interviews revealed critical insights into the emotional landscape surrounding chronic mental illness (CMI) management. Trust emerged as the dominant emotion across stakeholder groups, suggesting a foundation of confidence in mental healthcare fundamentals despite acknowledged limitations. This coexisted with prominent fear, particularly regarding diagnostic accuracy and care continuity, creating a tension between confidence in established frameworks and concern about their practical implementation.

Professional backgrounds significantly influenced emotional responses: clinicians demonstrated higher trust but also more anger, likely reflecting direct involvement in constrained care systems, while those with entrepreneurial backgrounds expressed greater anticipation and joy when discussing innovation possibilities. Discussions of current challenges consistently elicited negative sentiments, while conversations about innovation stimulated positive emotional responses. Our findings corroborate with a recently published narrative review (Leucht et al., 2024), which is critical of guidelines in psychiatric manuals like

DSM and ICD by focusing more on insurance payments rather than patient welfare.

The integration of sentiment analysis into CMI research offers promising opportunities for more patient-centered approaches that address not only clinical needs but also emotional experiences of patients, caregivers, and healthcare providers. Future research and analytics should include broader stakeholder perspectives, including those of a large number of patients and doctors, whose experiences are central to developing truly patient-centered approaches. Such an approach would bridge the gap between qualitative and quantitative analytics, where opinions from several experts at micromanagement levels will be available for policy making and patient-centric approach. With current computation capabilities, it is now possible to handle voluminous data, for instance 13,000 tweets (Shehu et al., 2020) using sentiment analysis and AI-models like random forest, support vector machine, maximum entropy, and decision tree to comprehend public viewpoint. Additionally, the potential of deep learning-based sentiment analysis models such as transformer architectures like BERT, RoBERTa will drastically improve contextual understanding and capture more nuanced sentiment beyond lexicon-based tools. This lays the foundation for future work integrating machine learning, deep learning and artificial intelligence-based approaches to complement our current methodology. We are firmly of the opinion that including sentiment analysis with other methodologies, including biomarker research, could create comprehensive frameworks addressing both objective and subjective dimensions of CMI experience.

A recent development in line includes incorporating the views of social sciences researchers going from DSM-IV to DSM 5. By acknowledging and addressing the complex emotional landscape surrounding mental healthcare, we can develop more holistic, responsive approaches that better serve individuals living with chronic mental illnesses and those who support them. Sentiment analysis reveals both challenges and opportunities in CMI management, providing valuable emotional dimensions that complement and enhance traditional qualitative analysis approaches.

CRediT authorship contribution statement

Abhishek Cukkemane: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Veralia Gabriela Sanchez:** Writing – review & editing, Validation, Supervision, Formal analysis, Conceptualization.

Declaration of competing interest

Both the authors declare no conflict of interest

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Supplementary materials

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