Exploring psychological topics and sentiments in how people tweet about chronic pain: A text-mining approach

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Author note

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"That's the thing about pain: it demands to be felt."

(John Green)

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Abstract

The physical, emotional and psychological complexities of chronic pain make it challenging to be assessed, managed and treated within the healthcare setting, as it involves various aspects of a patient's daily life. Automated content analysis utilising data from social media offers a new dimension to gain insights into patients' experiences. This study utilized three text-mining techniques, namely topic modelling, Sentiment Analysis, and Profile of Mood States (POMS) analysis, to gain insights into the challenges faced by individuals living with chronic pain, their emotional state, and mood patterns. The analysis was conducted on a dataset of 18,778 tweets containing the term "#chronicpain," collected from January 1 to February 28, 2023. A control sample of 2000 tweets was collected containing the term “I” for comparison purposes. The analysis identified five distinct topics, which were labelled by two researchers. These topics included (1) chronic pain and health, (2) living with chronic pain, (3) temporal aspects of chronic pain, (4) mental impact of chronic pain, and (5) medications and alternative therapies for chronic pain. The findings revealed a predominantly negative sentiment across five topics and a significant difference compared to the control group. The POMS results indicated that individuals living with chronic pain expressed high levels of depression, although the difference compared to the control group was not notable. Anger and fatigue scores were substantially higher in the chronic pain tweets than in the control tweets. This study highlights the potential of employing an exploratory text-mining approach to gain valuable and additional understanding of the psychological experience of health-related issues, such as chronic pain.

Introduction

Chronic pain is a highly prevalent problem on a global scale with about 20% of people worldwide living with chronic pain (Treede et al., 2015) and an estimated 10% new cases diagnosed each year (Goldberg & McGee, 2011). Chronic pain causes profound impacts on patients due to its complex and distressing nature. As defined in the International Classification of Functioning (ICF) chronic pain is continuous pain that persists longer than three to six months or beyond the regular recovery time for a specific injury (Treede et al., 2015). The impacts are on both the individual and social levels (Mills et al., 2019). Chronic pain causes long-term consequences relating to daily activities (Gureje et al., 1998; Nugraha et al., 2019; S. Y. Kim et al., 2019), physical (Lee et al., 2015; Treede et al., 2015; Mills et al., 2019; Eccles & Davies, 2021), psychological (Gambassi, 2009; Bushnell et al., 2013; Brennstuhl et al., 2015; Goesling et al., 2018; Meints & Edwards, 2018; Goesling et al., 2018; Kohrt et al., 2018), and social aspects of patients (Latham & Davis, 2009).

The main challenge related to chronic pain lies in the intricate psychological and social factors that come with living with this condition. Many chronic pain patients frequently experience mental health issues such as depression, anxiety, sleep problems, deterioration in the life quality, and high rates of other disabilities referred to as impairments, activity limitations, and participation restrictions (Nugraha et al., 2019). Previous studies have shown both a causal association and a strong bidirectional relationship between chronic pain and mental health (Hooten, 2016). Kroenke et al. (2011) studied 500 patients suffering from chronic pain and found that a change in pain severity predicts subsequent depression severity, and vice-versa. Half of the participants had comorbid depression. This suggests that pain and depression have reciprocal effects on each other over time. Linton (2000)'s systematic review of risk factors in back and neck pain showed that psychological factors were related to the initial stage of pain as well as the progress to chronic pain. Meanwhile, stress, distress, anxiety, mood and emotions, cognitive function, and pain behaviour have been identified as significant factors in pain progression from acute to chronic state. The psychological disorder frequently accompanies persistent pain, and this connection is observed across various cultural contexts (Gureje et al., 1998).

Psychological factors have been proven to influence how people experience pain and also treatment outcomes. The central themes that emerge from psychological factors related to pain are emotional responses and beliefs about pain (Linton & Shaw, 2011). Linton and Shaw proposed a “model of pain perception from a psychological view” which includes Attention (pain demands our attention), Interpretation (cognition process is used to interpret the pain), Emotions and emotion regulation (emotions that can influence the pain experience), and Behaviors (how people cope with the pain impacts their perception). Attitudes and beliefs about pain are factors associated with the progress of chronic pain, together with demographic, lifestyle, and clinical factors (Mills et al., 2019). Research suggests that assessing patients' beliefs about pain is vital for effective pain management. In the study by Linton & Shaw (2011), three pain-related beliefs linked to poor prognosis are pain catastrophizing, fear avoidance, and poor expectations for recovery. Self-efficacy, psychological distress, and fear avoidance have influences on pain mediating and disability relationships, suggesting that targeting these factors directly in treatment could be beneficial (Lee et al., 2015).

Psychological and social factors are responses to ongoing pain as well as an interconnected system of biological, psychological, and social processes that define chronic pain. Therefore, it's crucial to recognize these varied factors as “potential risk factors, protective factors, and process variables" in the dynamic system of chronic pain (Meints & Edwards, 2018). The roles of psychological assessment in chronic pain have been proved by identifying categories enhancing the diagnosis of underlying forms of pain, pain development, and discovering the mechanism responsible for pain (Williams, 2013). Research showed there is a significant need to address the biopsychosocial factors of chronic pain more effectively (Goesling et al., 2018). According to the ICF, understanding the complex problems of patients with chronic pain requires a holistic focus on the patient's experience, including psychological factors, the influence of the environment, or behavioural stereotypes (Nugraha et al., 2019). Understanding psychological factors and their impact on how people experience chronic pain potentially brings more opportunities to develop effective pain management, and provide psycho-education for patients to engage in self-care because, for most patients, chronic pain persists throughout a lifetime.

Research on people's psychological experiences when living with chronic pain often employs both quantitative and qualitative methods, such as interviews, ready-built questionnaires, and observation. Traditional methodologies offer certain advantages and drawbacks. Surveys provide structured data collection but may lack real-life context and be prone to potential biases, while qualitative studies offer in-depth understanding but often have limited sample sizes and may lack generalizability. Both methodologies are subject to limitations, including recall bias, non-real-life settings, and the need for substantial resources. When it comes to utilizing Big Data, traditional methodologies may struggle with large-scale analysis, efficiency, speed, as well as the ability to uncover hidden insights and objective outcomes. Big Data analysis offers the potential to overcome these limitations by leveraging vast amounts of data, but it requires new approaches and tools to extract meaningful information from complex datasets.

With the growth of the population proportion using social media, the source of available unstructured digital data nowadays is massive, offering researchers novel access and materials to gain new insights into the mental health field (Chen & Wojcik, 2016), including people's experiences of health issues. Ressler et al. (2012) examined the effect of writing about chronic pain and illness in blogs and found that writing and sharing on blogs could alleviate feelings of loneliness by forming virtual connections with people online, and also increase a sense of motivation to assist others in similar circumstances. Lachmar et al. (2017) examined 3225 tweets with hashtag #MyDepressionLooksLike, and after analysis, seven themes emerged: "dysfunctional thoughts, lifestyle challenges, social struggles, hiding behind a mask, apathy and sadness, suicidal thoughts and behaviours, and seeking relief". Ma & Stahl (2017) collected and analyzed 122 posts with 1456 comments from a Facebook group. The posts contained sentimental rhetoric and graphic information about vaccine injury. The study identified four attributes (sentimentality, reductionism, tautology, and insularity) that influenced parental information-seeking and sharing on Facebook. van Kampen et al. (2022) employed Tiktok data to examine the top 100 videos on TikToks with the hashtag #covidvaccine and the result showed that out of the 102 videos analyzed, 14.7% included healthcare professionals (HCPs), with 80% of them being verified. All videos created by HCPs supported vaccine use, and in total, 81.3% of all videos supported vaccine use. Compared to traditional research methodologies, data from social media reflects naturalistic social interaction, large-scale behaviours, and self-expression content, together with specific location and real-time records, making it advantageous for the public health research (Wang et al., 2016). Also, these studies do not suffer from some of the disadvantages that surveys or interview methodologies face such as low response rates and challenges in collecting data on sensitive topics. In a recent study, Sarker et al. (2023) reveals that social media is a valuable information source for chronic pain research.

Among social media platforms, Twitter, a computer-mediated online communication platform launched in 2006, is one of the most popular platforms. As of December 2022, Twitter’s audience accounted for over 396 million users worldwide (*The Latest Twitter Statistics*, n.d.). Twitter provides a unique big data source for researchers due to its publicly available and generated real-time content. The short and textual focus of Twitter, was originally limited to 140 characters and later expanded to 280 characters per tweet in 2017. Notably, as of the time of writing, Twitter has announced plans to increase the character limit to 10,000 per tweet for Twitter Blue accounts commencing in April 2023. Twitter Blue is a premium subscription service that provides users with a blue checkmark, early access, and additional features (*About Twitter Blue*, n.d.). This study examined tweets from the period between January and February 2023, During this timeframe, the character limit for each tweet adhered to 280 characters. Twitter's diverse user base, spanning various age groups, allows researchers to examine content from different perspectives and study topics across different cohorts. The real-time nature, accessibility, and volume of Twitter data make it a valuable resource for content analysis. Several research topics have been studied using data from Twitter including politics, stock market, health discussion, disease surveillance, sport, entertainment, drugs, and information behavior (Karami et al., 2020). In the field of psychology research, Twitter data is also being increasingly used to study various psychological phenomena. For example, Twitter data has been utilized to examine the ruminating behaviour of depression by conducting emotional analysis through opinion mining (Nambisan et al., 2015), predicting county-level heart disease mortality

(Eichstaedt et al., 2015), exploring the language of users with a wide range of mental health conditions (Coppersmith et al., 2015), analyzing trends in work stress and emotion (Wang et al., 2016), or to detect hot research topics in psychology research (Bittermann et al., 2021).

Despite the prevalence of chronic pain-related discussions on Twitter, this resource remains largely untapped in epidemiological and interventional research (Sarker et al., 2023). Additionally, Kloth et al. (2019) also revealed that individuals experiencing pain express themselves differently on Twitter compared to in healthcare settings. This study uses an automated data-mining technique, called Text mining, which is suitable to derive and analyze unstructured big data from Twitter. In health-related research, text mining offers an alternative automated approach for gathering and analyzing data about patients' experiences, and overcomes some of the limitations of formative evaluation methods using elicitation techniques or survey and consultation (Bicquelet, 2017). In this study, three text-mining techniques, topic modelling, sentiment analysis (SA), and Profile of Mood States (POMs) are employed to explore the potential of analysing Twitter data related to chronic pain topics. The aim is to explore the central themes individuals tweet about regarding chronic pain, with a focus on psychological aspects. By analysing their emotional experiences associated with these issues, the researcher aim to learn about the psychological impact of chronic pain as expressed through their Twitter activity.

Research background and related works

Previous studies have demonstrated the valuable findings achieved through text mining in the domain of chronic pain topics. For instance, Nunes et al. (2022) employed topic modeling to analyze pain descriptions from interview transcripts, utilizing external semantic relations to enhance understanding of chronic pain. The results provided relevant insights for clinical assessment and management, including the identification of crucial aspects of pain and the grouping of patients based on their descriptions. Goudman et al. (2022) examined discussions on the social media platform Reddit related to chronic pain. The analysis revealed common terms used by patients, with '*pain'* being the most prevalent, followed by terms like '*doctor', 'day', 'feel', 'back', 'year*', and '*time'*. Back pain emerged as the most frequently mentioned location. Tighe et al. (2015) conducted a study utilizing text-mining techniques to explore pain-related tweets across 50 cities. The results indicated variations in sentiment among cities and posting hours and the presence of emotional terms was greater in pain-related tweets such as *"tired", "happy", and "sad*", compared to objective terms. The study also revealed differences in social network characteristics in pain-related tweets compared to other common terms, including lower connectedness and greater sparsity (Tighe et al., 2015). Another study from Bicquelet (2017) applied text-mining to analyse YouTube video comments about chronic pain and found that online forums, specifically YouTube, contain a wealth of information that is difficult to obtain through traditional research techniques (Bicquelet, 2017). This may be because individuals may feel more comfortable expressing themselves online openly, and disclosure of information that may not be readily obtainable through conventional research methods. Another study by Mullins et al. (2020) analysed pain-related tweets on Twitter in Ireland over two weeks and found that the most frequently mentioned pain-related keywords were "*headache", "migraine", "back pain", "cannabis",* and *"chronic pain"*. The majority of tweets came from female users. Cannabis-related tweets had a highly positive sentiment and received the highest number of impressions per tweet. These studies highlight the value of text mining in uncovering insights related to chronic pain topics and offer opportunities for improved understanding and management of pain conditions.

Although several studies have studied chronic pain using Twitter data, research on using Twitter data to explore the psychological aspects and sentiments related to chronic pain remains limited. In order to have a comprehensive examination, it would be beneficial to include a comparative analysis between chronic pain-related data and control data, to gain an understanding of the unique psychological challenges and how sentiments associated with chronic pain differ from control data. With the application of text-mining techniques, incorporating a comparative analysis, this study seeks to delve deeper into the living experiences of individuals with chronic pain and uncover valuable insights that can inform clinical assessment and provide support for those coping with chronic pain. To achieve these goals, the study will explore the following research questions:

RQ1: *What psychological themes emerge from tweets related to chronic pain?*

RQ2: *What are the sentiments expressed in these tweets associated with each theme?*

RQ3: *What are the profiles of mood states associated with each theme?*

Methods

Text mining, alternatively known as text data mining, is the application of machine learning and statistics to textual data to identify useful patterns (Hotho et al., 2005). Therefore text mining is used to gain insights and identify noteworthy patterns and connections within vast amounts of textual data (Feldman & Sanger, 2007). Text mining combines approaches from "information retrieval, information extraction, and natural language processing (NLP), and integrates them with algorithms and methods from knowledge discovery in databases (KDD), data mining, machine learning, and statistics" (Hotho et al., 2005). Common text-mining tasks include categorizing, clustering, extracting concepts, generating detailed taxonomies, analysing sentiment, summarizing documents, and modelling relationships between named entities (Text Mining, 2023).

Software

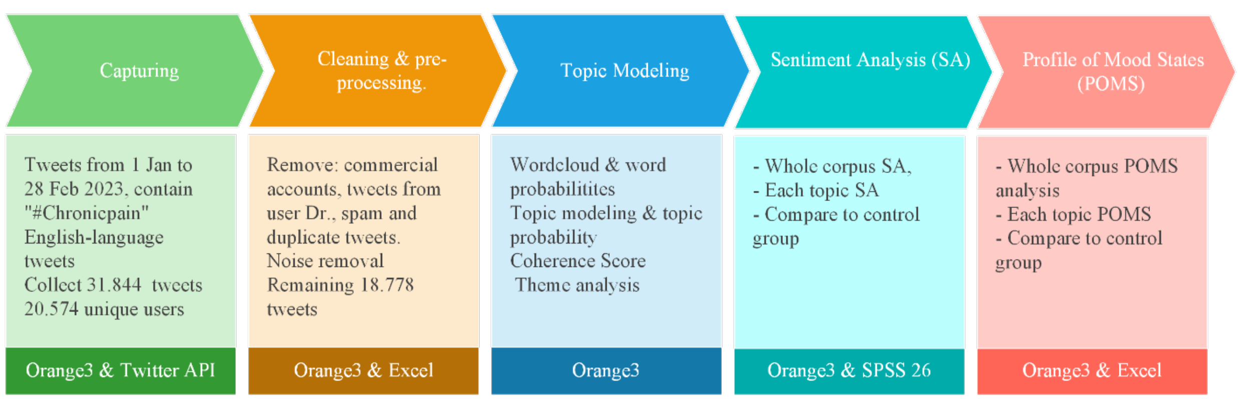
This study used Orange Data Mining version 3.34 (University of Ljubljana, Slovenia). Orange is a Python-based software with open-source machine learning and data visualization using a graphic user interface that allows users to focus on exploratory data analysis without requiring coding experience and knowledge. Orange makes the prototyping process of a data analysis workflow easy to use by placing widgets on the canvas, connecting them, loading the datasets, and viewing the result (Ljubljana, n.d.). The statistical software platform IBM® SPSS® version 26 was used for additional descriptive and statistical analyses.

Study Design

Text-mining consists of several consecutive steps to obtain meaningful information from unstructured texts like Tweets. The data collection, preparation, and analysis stages followed in the current study are summarized and visualized in Figure 1.

Figure 1

Study Design



Data Capturing

Tweets were scraped with the Orange Twitter widget, which uses a Twitter API to search Tweets for certain keywords. Original Tweets were collected that were posted between the first of January to the 29th of February 2023 and that used the hashtag *"#chronicpain*". Due to Twitter's data limitation policy, researchers with a non-commercial API can only retrieve tweets up to seven days in the past during each search, so the search was repeated every week for two months. Two months of tweets were scrapped because initial scraping exercises suggested that a two-month window would provide sufficient conversations about chronic pain. Secondly, the number of tweets within a two-month frame was considered to be still computationally manageable for content analysis using topic modelling. The purpose of scraping only tweets containing the specific hashtag *#chronicpain* was to collect only the most relevant content. Retweets were not included so that the original tweets only account for one time in the analysis process. The data collected included the tweet contents and user meta information, including time published, a numeric Tweet ID, nominated location, and specific language. Only English-language tweets were included. In the end, this resulted in a total number of 31,844 original tweets from 20,574 unique users.

To establish a baseline comparison for evaluation and improve the interpretability of the findings, the sentiment analysis (SA) and Profile of Mood States (POMS) results were compared to a control data set. The control data consisted of 2000 tweets gathered from Twitter on May 28th, 2023, containing the term "*I."* This comparison allows for more meaningful analysis and validation of the sentiment outcomes of chronic pain tweets against non-specific tweets.

All data were collected and reported in compliance with the terms and conditions of Twitter, which permit public access and sharing of content posted by individuals to syndicate, broadcast, distribute, retweet, promote, or publish while excluding private information (*Twitter Privacy Policy*, n.d.)

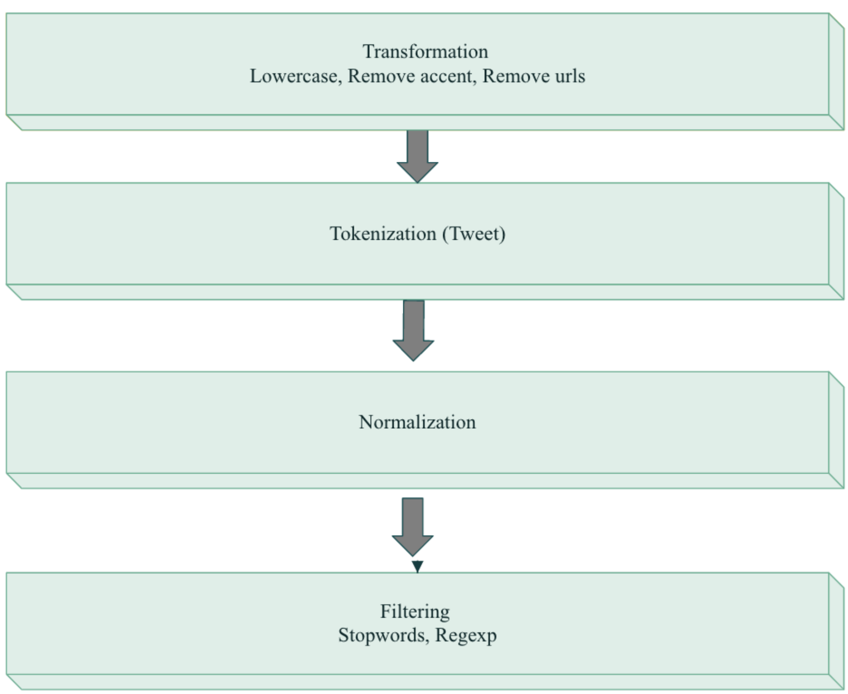
Cleaning and pre-processing

To obtain a patient-generated dataset from individuals who tweet about their chronic pain, the study preserved tweets that reflected the perspectives and experiences of individual users. The cleaning process in this study included four steps. Firstly, 446 tweets from commercial accounts associated with magazines, organizations, and institutions were eliminated by applying a filter to exclude verified accounts (those with blue badges) that were followed by more than 10,000 accounts. Additionally, 369 tweets were removed by filtering user accounts with names containing "Dr". The exclusion aimed to prioritize user-generated content that reflects personal experiences and perspectives on chronic pain, while specifically excluding tweets from healthcare professionals (The list of these removed accounts can be found in Appendix 1). Furthermore, 11,730 tweets containing the link "https://" were excluded. Lastly, 520 spam and duplicate tweets (those posted more than once by the same user) were eliminated. After these removal steps, 18,778 tweets remained available for analysis.

Preprocessing of raw textual data (Figure 2) is required for most text-mining techniques because, in contrast to humans, the computer cannot read meaningless textual elements. Initially, the data was processed by transforming, after which various techniques such as tokenization, normalization, and filtering were applied. The transformation stage converted all text into lowercase, removed accents, and removed URLs. The tokenization stage broke the text into smaller components using the standard Tweet option in Orange. The next task was to normalize words by applying stemming and lemmatization to words. In this study, the Snowball stemmer was applied (*Snowball*, n.d.). Stemming is a process that assigns a common "stem" to various forms of the same word. For example, the English stemmer links the words jumping", "jumps", "jumped", and "jumper" to the stem word "jump". This means that if a search query contains any of these variations, the algorithm will retrieve documents containing the stem word "jump". The final step is filtering. By examining a word cloud, this study created a customized stop word list *(Appendix 2)* to remove words that were still prevalent in the word cloud but did not contribute meaningful information to the analysis. By excluding these stop words, we aimed to enhance the interpretability of the analysis. The study applied a regular expression (regexp) setting to remove punctuation marks from the text. Regular expressions are a versatile tool that enables efficient and precise text manipulation by specifying patterns to match within a given text (*Regular Expression Tutorial - Learn How to Use Regular Expressions*, n.d.)

Figure 2

Data Pre-processing pipeline



Data-mining and Analysis

Topic modelling

Topic modelling is an approach widely used in computational linguistics for analyzing topics from a large archive of literature (Griffiths et al., 2007) to discover the main themes emerging from big unstructured data (Tong & Zhang, 2016), based on clusters of words found in each document and their appearance frequency. The aim of applying topic modelling in the current study was to find out if specific psychological themes can be identified that underlie the tweets and which themes are mostly mentioned in chronic pain-related tweets. It is important to note that a tweet is often composed of multiple topics, each with varying degrees of prevalence. As such, the Topic Modelling widget also provides information on the weight of each topic within a given document.

Topic modelling with Latent Dirichlet Allocation

Topic modelling allows for the identification of underlying patterns and topics in large sets of Twitter data without prior knowledge of the topics being discussed. The most common and popular topic modelling algorithms are Latent Dirichlet Allocation (LDA), Latent Semantic Indexing (LSI), and Hierarchical Dirichlet Processing (HDP).

Latent Dirichlet Allocation (LDA) is a probabilistic topic modelling technique that operates under the assumption that words that appear together in a document are more likely to be related to the same topic (Negara et al., 2019). LDA postulates that documents sharing common words are more likely to belong to the same topics and determines which topics tweets belong to by looking at the word co-occurrences, based on the words they contain. Similar to LSI, LDA can be viewed as a dimensionality reduction technique that reduces the dimensionality of a high-dimensional text data space (D. Blei et al., 2001). However, unlike LSI, LDA with "its simple exchangeability assumption for the words and topics in a document" is based on underlying generative probabilistic semantics that makes it more suitable for handling unstructured data (D. M. Blei, n.d.). A recent study showed that LDA is efficient for analysing tweet data. It excels in tasks such as topic extraction, modelling, generating index words for each topic, and presenting the results in visualizations. LDA has shown excellent performance in word indexing for sports topics, using a dataset of 1260 tweets with 98% accuracy, outperforming the LSI method in the topic modelling (Negara et al., 2019). LDA can additionally make use of Twitter-specific tokens such as neologisms and emoticons and phrases that convey meaning and psychological insights (Murphy, 2017).

The Hierarchical Dirichlet Process (HDP) was first introduced by Teh in 2006. HDP is a nonparametric Bayesian method used for modelling grouped data by linking mixture models through a nonparametric prior. It provides a hierarchical structure for modelling mixture models, making it useful for analysing complex data (Teh et al., 2006). Due to HDP's complexity and computational requirements, HDP is efficient to handle large and complex datasets in long documents. However, the short length and limited vocabulary of tweets may not provide enough information to accurately infer the underlying topics. Therefore, LDA was applied in this study for analysing tweets.

Coherence score

To evaluate the optimal number and interpretability of the resulting topics after analyzing the set of data from 18,778 tweets related to chronic pain, coherence scores were computed for increasing numbers of topics. Topic coherence was used to examine the interpretability of the topic modelling output via coherence scores across different numbers of topics (Rosner et al., 2013). A coherent topic model should produce topics with words that are as close as possible related in meaning. The coherence score is used to evaluate the quality of topic models by comparing the similarity of the words in the topics (Zvornicanin, 2021). Comparing coherence scores for different numbers of topics can determine the optimal number of topics that results in the most coherent and interpretable topics. To accomplish this, coherence scores were plotted to examine how the coherence scores change as the number of topics increases. Based on this plot, and the interpretability of the resulting topics, the optimal number of topics was determined. The decision was guided by using an elbow method, which identifies a point on the plot where additional topics do not yield substantial improvements in coherence scores. By selecting this point, it ensures that the resulting topics are both coherent and insightful.

After determining the number of topics, the labelling process for assigning themes to the identified topics involved the collaboration of two researchers to ensure objectivity and minimize potential bias. The second researcher was a psychology master's student who was trained in text mining. Each researcher independently labelled the themes associated with the topics. The assigned labels were compared and any discrepancies were resolved through consensus.

Sentiment analysis (SA)

Sentiment analysis (SA), also known as opinion mining, is used to explore human opinion and attitudes toward specific topics without the need for manual analysis. There are two main approaches used in SA, the lexicon approach and the machine learning approach (Hutto & Gilbert, 2015).

In Orange, the lexicon approach is applied. The lexicon approach is dictionary-based in that it compares the text in a corpus with the sentiment scores to a reference word list or "prior-polarity lexicon", an existing dictionary that contains lists of positive and negative text. The lexicon approach can work with phrases, negations, and punctuation. The results usually report positive, negative, and neutral scores and a final compound score. Several commonly used sentiment modules are available, including VADER sentiment analysis, Liu & Hu sentiment analysis, and other sentiment modules.

Hutto and Gilbert compared the VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment lexicon to “seven other established sentiment analysis lexicons (Linguistic Inquiry Word Count (LIWC), General Inquirer (GI), Affective Norms for English Words (ANEW), SentiWordNet (SWN), SenticNet (SCN), Word-Sense Disambiguation (WSD) using WordNet, and the Liu & Hu opinion lexicon)” finding that VADER performed exceptionally well in analyzing sentiment in social media and showed favourable generalization (Hutto & Gilbert, 2015). Taking into account the unstructured characteristic of Twitter data, this study applied VADER, a lexicon-based sentiment analysis tool that is designed for analyzing informal language.

The sentiment score in VADER is computed by assigning polarity scores to the words in the text, ranging from -1 (most negative) to +1 (most positive), with 0 denoting a neutral sentiment. The tool also provides a compound score. A compound score of 0 indicates a neutral sentiment, while a score closer to +1 or -1 indicates a stronger positive or negative sentiment, respectively. VADER has proven to be particularly effective in social media contexts and can generalize well to other domains (Hutto & Gilbert, 2015)

A two-step approach of sentiment analysis was conducted. The first step involved comparing the compound scores of the tweets with the control dataset to examine the overall sentiment of the tweets in relation to a baseline and to identify if there are any notable differences between the sentiment of the tweets in the dataset and the baseline established by the control data. The second step delved deeper into the sentiment analysis by examining the sentiment distribution across topics present in the chronic pain tweets.

SPSS was employed to categorize each tweet into one topic based on their highest prevalence score. The prevalence score indicated the probability of a tweet belonging to one of the identified topics, with higher scores indicating a higher likelihood of association with that specific topic. Next, a one-way analysis of variance, with post hoc Least Significant Difference (LSD) tests, was conducted to test for differences in mean compound sentiment scores across the topics. This allowed for a deeper understanding of the sentiment distribution and differences among the topics.

Profile of Mood States

Profile of Mood States (POMS), developed by McNair, Droppleman, and Lorr in 1971, is a psychological tool used to assess mood states from documents. It is based on a set of sixty-five adjectives, which are rated on a five-point scale to indicate how much the individual feels each emotion (McNair, 1971). POMS categorizes mood states based on emotions categories: Tension, Depression, Anger, Vigor, Fatigue, and Confusion (Norcross et al., 1984).

This study used automated POMS analysis by applying the Tweet Profiler widget. The widget is utilized to gather sentiment-related data for each tweet or document. The widget transmits the collected data to the server, which employs the POMS algorithm to calculate the probabilities of various emotions. The output is emotion probabilities.

This study employed POMS because it was suitable for assessing individuals' mood states (Norcross et al., 1984). The Orange widget supports three classifications of emotion, including Ekman's, Plutchik's, and POMS. Ekman defined joy, sadness, anger, surprise, fear, and disgust based on facial expression (Ekman, 1992). Plutchik added two additional emotions and developed a wheel of emotions, including Acceptance, Anger, Anticipation, Disgust, Joy, Fear, Sadness, and Surprise (Plutchik, 1980). Orange supports multi-class and multi-label settings. In the multi-class setting, the output provides the most probable emotion for each tweet. In a multi-label setting, the output presents values in separate columns for each emotion, indicating the presence or absence of that particular emotion for each document.

To evaluate whether there are notable differences in mood states between those tweets discussing chronic pain and non-specific tweets, and to explore if there are unique emotional challenges faced by individuals living with chronic pain, a comparison with POMS scores for the control data of tweets containing the term “I” was performed.

Result

The following section presents the results obtained from the final general word cloud, topic modelling, SA, and POMS analysis.

Word cloud

Figure 3 shows a visualization of the most frequent terms in the processed data. The word size indicates their frequency. The terms *"pain"* and *"chronic*" appear at the top of the list because they are the search terms. *“Amp”* is the third frequent term. On Twitter, *"amp"* may be the short form for "amplify" or "ampules". The researcher screened tweets containing *“amp”* and found that *"amp"* was mainly an amplification of pain sensations. The word *"patients"* appears in the top four, suggesting that tweets may have been generated from patient testimonials or feedback. Other time-related terms such as *“life”, “time”, “years”, “year”, “days”, “day”, “today”, “everyday”,* and *“since”* reflect the long-term or fluctuating nature of chronic pain and its impact on people's daily lives. Other notable themes include mental health, with *"anxiety",* *"depression"* and *"mental"* appearing frequently. The use of painkillers including *"meds", "opioid", "opioids"* and *"medication"* is also mentioned. The frequency of words such as *"illness," "health,", "doctor"* and *"care"* suggests that there may be a focus on healthcare and treatment. The physical-related terms such as *"back", "body", "physical",* and *"fatigue"* highlights the impact of chronic pain on body parts and functioning. Words *"help", "helps", "need", "suffer", "suffering", "severe"* and *"hard"* indicate common themes of despair and helplessness in chronic pain. The importance of finding relief from pain is also evident, as words like *"relief," "help,"* and *"treatment"* are high on the list as well.

Figure 3

The Pre-processed Word Cloud of 18,778 Tweets with #chronicpain

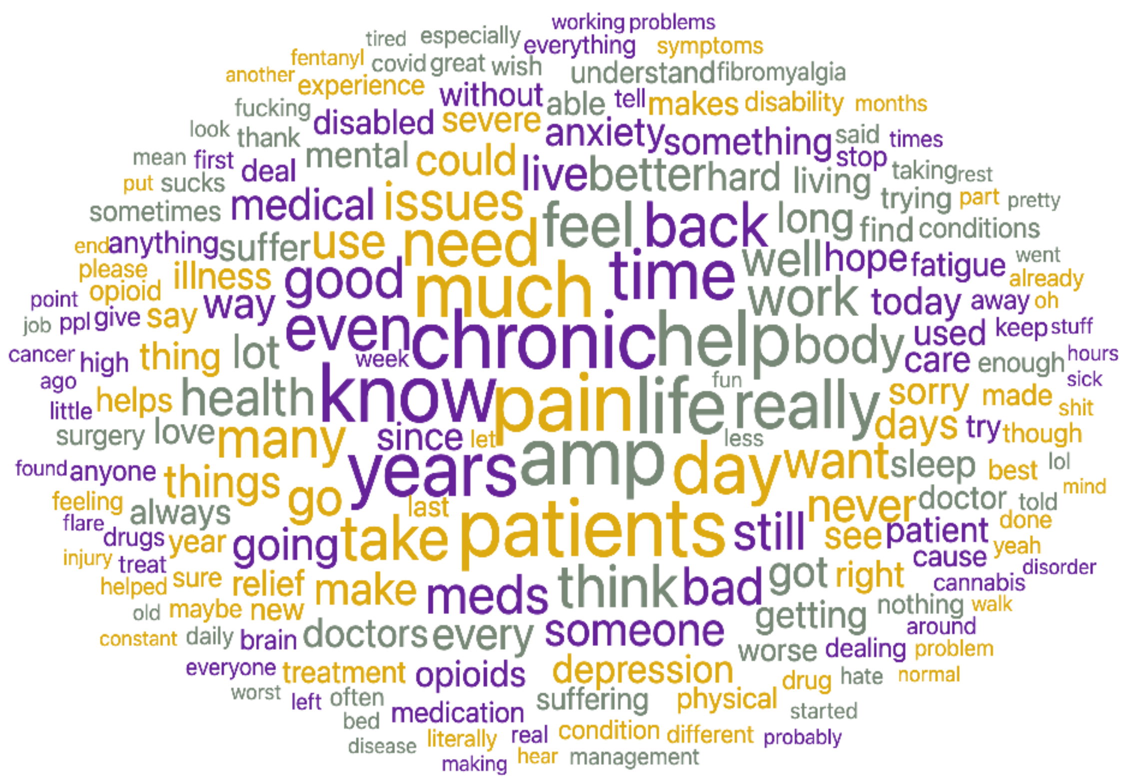


Table 1

100 Most Frequent Words

Words	Weight	Word	Weight	Words	Weight	Words	Weight	Words	Weight
pain	24263	work	862	medical	665	illness	546	doctor	451
chronic	19895	issues	833	got	661	care	533	year	445
amp	2530	meds	833	could	658	mental	524	try	443
patients	1448	body	827	way	650	severe	522	worse	435
know	1330	want	817	long	636	opioids	519	new	427
life	1279	still	814	days	623	love	516	deal	423
much	1266	health	813	anxiety	587	right	514	suffering	416
years	1263	go	805	hard	580	used	511	treatment	414
help	1242	bad	796	see	577	living	511	anything	412
day	1178	well	764	hope	577	relief	507	understand	411
time	1145	use	762	doctors	576	patient	503	made	403
really	1091	live	742	depression	573	always	502	cause	399
need	1064	better	729	since	573	say	502	trying	399
even	1038	never	729	suffer	563	disabled	479	physical	390
feel	991	someone	710	sorry	559	find	476	medication	380
take	990	lot	709	today	557	helps	476	sometimes	379
back	983	make	688	sleep	556	without	466	last	376
think	931	going	684	thing	556	able	466	anyone	374

Table 1 ***(Continued)***

Words	Weight	Word	Weight	Words	Weight	Words	Weight	Words	Weight
many	892	every	682	something	553	makes	464	surgery	373
good	887	things	681	getting	550	fatigue	460	opioid	370

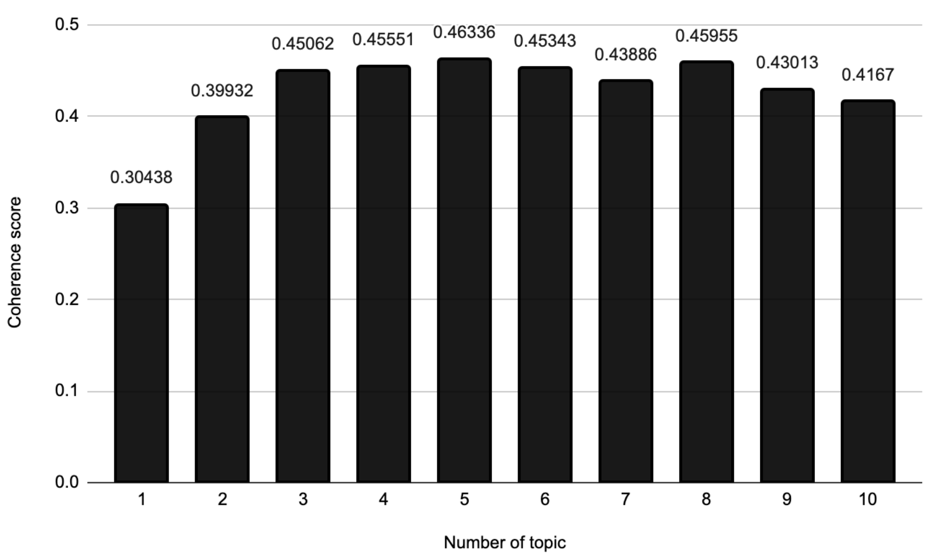
Notes. Weight represents the absolute number of times terms are used

Topic Modelling

The coherence score plot for determining the optimal number of topics is presented in Figure 4 for the first ten topics. The coherence score reached its top at the number of five topics, at 0.463, after which coherence scores seemed to decrease again with increasing number of topics. As five topics also appeared to be sufficient for interpretable and saliently unique topics, five topics were selected for further analyses.

Figure 4

Topic Coherence Scores Plotted for Topic Numbers Ranging from 1 – 10



Topic 1 consists of 1286 tweets. For topics 2, 3, 4 and 5 the number of tweets are 386, 10617, 3391 and 3097, respectively. Table 2 shows the results of a topic modelling analysis with the lists of the dominant keywords associated with each topic and the topic size, represented as a percentage of the total tweets analysed. Topic 3 has the largest size, representing 43.70% of the tweets analysed. Topic 2 was the smallest, with 5.71% of the tweets belonging to this topic.

Table 2

Dominant Keywords of the 5 Topics with Topic Sizes

Topics	Domimant keywords	Topic size
1	chronic, pain, amp, sleep, anxiety, weight, health, yesterday, depression, ass	9.43%
2	chronic, pain, question, pls, weekend, sore, syndrome, heat, asleep, local	5.71%
3	pain, chronic, day, much, today, really, know, time, feel, life	43.70%
4	pain, chronic, amp, health, years, life, depression, mental, even, disabled	20.02%
5	pain, chronic, patients, meds, amp, patient, opioids, many, doctors, use	20.17%

The five topics were independently interpreted and labelled by two researchers by incorporating semantic similarity of the dominant keywords and a focus on psychological insights. Both researchers came up with the same themes to the topics, with slight differences in wording. The second researcher suggested as following:(1) Mental and physical health, (2) Restriction due to symptoms, (3) Time and progression of pain, (4) Mental health, and (5) Medication and treatment. The researcher manually screened through tweets to ensure the themes effectively capture the essence of the content within each topic. Finally, these themes were labelled as follows: (1) chronic pain and health, (2) living with chronic pain, (3) temporal aspect of chronic pain (4) mental impact of chronic pain, and (5) medications and drugs for chronic pain.

Table 3

Five Topics from Tweets Related to Chronic Pain and Word Probability.

Topic	Word probability
Chronic Pain and Health	Chronic (0.0430), pain (0.0405), amp (0.0142), sleep (0.0066), anxiety (0.0055), weight (0.0055), health (0.0041), yesterday (0.0041), depression (0.0040), ass (0.0039), symptoms (0.0039), helps (0.0037), requesting (0.0036), use (0.0035), issues (0.0034), fatigue (0.0032), inflammation (0.0030), rn (0.0030), blood (0.0028), medical (0.0026)
Living with Chronic Pain	Chronic (0.0077), pain (0.0063), question (0.0042), pls (0.0032), weekend (0.0029), sore (0.0027), syndrome (0.0026), heat (0.0026), asleep (0.0024), local (0.0023), girl (0.0022), yo (0.0022), massive (0.0021), everywhere (0.0019), relieve (0.0019), liver (0.0018), couch (0.0018), cases (0.0018), restrictions (0.0017), spinal (0.0017)
Temporal aspect of chronic pain	Pain (0.0858), chronic (0.0709), day (0.0085), much (0.0069), today (0.0065), really (0.0063), know (0.00622), time (0.0059), feel (0.0058), life (0.0053), back (0.0051), help (0.0050), bad (0.0050), body (0.0046), want (0.0045), take (0.0044), even (0.0042), good (0.0042), think (0.0042), days (0.0041)
Mental Impact of Chronic Pain	Pain (0.0561), chronic (0.0497), amp (0.0083), health (0.0052), years (0.0050), life (0.0049), depression (0.0045), mental (0.0041), even (0.0039), disabled (0.0038), physical (0.0036), issues (0.0035), trauma

Table 3 *(Continued)*

Topic	Word probability
Mental Impact of Chronic Pain	(0.0033), illness (0.0033), work (0.0032), things (0.0030), long (0.0030), anxiety (0.0029), still (0.0029), since (0.0029)
Medications and Drug for Chronic Pain	pain (0.0611), chronic (0.0407), patients (0.0165), meds (0.0079), amp (0.0077), patient (0.0064), opioids (0.0059), many (0.0053), doctors (0.0050), use (0.0048), medication (0.0045), need (0.0040), medical (0.0039), opioid (0.0039), drugs (0.0037), drug (0.0035), treatment (0.0034), doctor (0.0032), care (0.0030), treat (0.0029)

**Note.* Probability of a word belonging to a topic represented as percentage of total words within a topic.

Theme 1: Chronic pain and health

This wordlist pertains to chronic pain and health. The word *"amp"* (0.0142) is a short for amplification of pain sensations. The words *"sleep"* (0.0066) and *"fatigue"* (0.0032) suggest a notable impact on an individual's sleep patterns and energy levels,. The word *"health"* (0.0041), "*weight*" (0.0055), *"inflammation"* (0.0030), "*blood"* (0.0028), *"symptoms"* (0.0039), and *"issues"* (0.0034) suggest that maintaining overall health is a key concern for individuals with chronic pain and that chronic pain can have a wide range of negative impacts on health. The word *"anxiety"* (0.0055) and *"depression"* (0.0040) highlights the emotional consequences of chronic pain. The word *"helps"* (0.0037), *"requesting"* (0.0036), *"medical"* (0.0026), and *"rn"* (0.0030), which is an abbreviation commonly used to represent "right now", suggests that individuals with chronic pain are in urgent need to seek medical treatment.

Theme 2: Living with chronic pain

Individuals living with chronic pain often encounter difficulties managing their symptoms, seeking effective treatments, and coping with the emotional and psychological consequences of their condition. The words *"massive"* (0.0021), *"restrictions"* (0.0017) and *"everywhere"* (0.0019) emphasize the pervasive and overwhelming nature of chronic pain. The presence of the word *"question"* (0.0042) may suggest that individuals with chronic pain may experience uncertainty and doubt surrounding their condition. This uncertainty may be compounded by the abbreviation *"pls"* (0.0032) which reflects a desperate plea for assistance that individuals with chronic pain may express. The words *"sore"* (0.0027), *"syndrome"* (0.0026), *"heat"* (0.0026), *"asleep*" (0.0024), *"liver"* (0.0018), and *"spinal"* (0.0017) reflect some aspect related to their pain symptoms. The word *"weekend"* (0.0029) may be interpreted as indicative of the challenges that individuals with chronic pain may face when trying to balance their condition with social and entertainment activities. It can be also interpreted that weekends are utilized as a time to rest and recuperate. The presence of the word *"couch"* (0.0018) might indicate that individuals with pain tend to spend a significant amount of time resting on the couch due to their discomfort. The presence of the word *"relieve"* (0.0019) suggests that effective pain management is a key concern for individuals with chronic pain.

Theme 3: Temporal aspect of chronic pain

The theme "Temporal aspect of chronic Pain" highlights the persistent challenges and complexities associated with chronic pain, emphasizing the role of time, such as chronicity and fluctuations, in the experience of pain. The high probability of words such as *"time"* (0.0059), *"day"* (0.0085), *"today"* (0.0065), and *"days"* (0.0041) reflect the importance of time in pain experience, highlighting the daily struggles people living with chronic pain face. Words such as *"much"* (0.0069), *"really"* (0.0063), *"bad"* (0.0050), and *"even"* (0.0042) indicate the intensity and severity of the pain, while *"help"* (0.0050) suggests that individuals with chronic pain are in need of support. The word *"life*" (0.0053) emphasizes the significant impact that chronic pain has on an individual's quality of life. The presence of verbs *"know"* (0.00622), *"feel"* (0.0058), *"want"* (0.0045), *"take"* (0.0044), and *"think"* (0.0042) indicate chronic pain creates ongoing cognitive and emotional processes in individuals on how to manage the condition over time.

Theme 4: Mental Impact of Chronic Pain

The theme includes words such as *"amp"* (0.0083), *"health"* (0.0052), *"depression"* (0.0045), *"anxiety"* (0.0029), *"mental"* (0.0041), *"disabled"* (0.0038), *"physical"* (0.0036), *"issues"* (0.0035), *"trauma"* (0.0033), and *"illness*" (0.0033) highlight the multifaceted nature of chronic pain and its mental impact on an individual's well-being. Additionally, the words *"years"* (0.0050), *"life"* (0.0049), *"work"* (0.0032), *"things"* (0.0030), *"long"* (0.0030), *"still"* (0.0029), and *"since"* (0.0029) underscore the persistent nature of chronic pain and its impact on an individual's ability to carry out daily tasks, work, and socialize. The high probability values associated with these words further indicate their significance in understanding the mental impact of chronic pain.

Theme 5: Medication and alternative therapies:

This theme focuses on the different medications and alternative therapies that are used to manage chronic pain. *"Patients"* (0.0165) and *"patient"* (0.0064) indicate the focus on the individuals who are in need of medical intervention. The term *"amp"* (0.0077) is abbreviation for pain amplification. *"meds"* (0.0079) are abbreviation of medications. *"Opioids"* (0.0059), *"opioid"* (0.0039), *"drugs"* (0.0037), and *"drug"* (0.0035) suggest the prevalence of opioid medications and other drugs in chronic pain treatment. *"Doctors"* (0.0050), *"medical*" (0.0039), *"doctor"* (0.0032), *"care"* (0.0030), *"treatment"* (0.0034) and *"treat"* (0.0029) emphasize the crucial role that healthcare providers play in medications and drugs for chronic pain and the need for comprehensive plans that address the multifaceted nature of chronic pain.

Sentiment Analysis

Compound Scores comparison with control data

Table 4 highlights the compares the compound sentiment scores observed in in the chronic pain-related tweets and control tweets. The mean sentiment score of -0.3980 in the chronic pain tweets indicate predominantly negative sentiment. Conversely, the mean sentiment score of 0.1804 in the *"I"* data in control group suggests positive sentiment. The standard deviations of 0.5304 and 0.4992 for the "Chronic pain" and "Control" groups, respectively, indicate similar levels of variability in sentiment scores within each group. An independent t-test was conducted to compare the mean compound scores between the 'Chronic pain' dataset and the 'Control data' dataset. The results of the t-test analysis demonstrated a substantial difference between these two groups ($t = -22.7613$, $df = 20776$, $p < 0.001$).

Table 4

Comparing Compound Scores between Data Set and Control Data

	Mean	**SD**
Chronic pain	-0.3980	0.5304
Control data	0.1804	0.4992

Note. Mean: medium sentiment score, SD: Standard Deviation

Analyzing Sentiment by Topics

Table 5 shows the predominance of negative sentiment in tweets related to chronic pain across all topics. The mean scores range from -0.375 for Topic 1 to -0.420 for Topic 5, with an overall mean score of -0.398 for the entire dataset. Topic 1 has the highest standard deviation of 0.545, while Topic 2 has the lowest standard deviation of 0.518.

Table 5

Mean Compound Sentiment Scores of Five Topics Related to Chronic Pain

Topic	N	Mean	SD
1	1286	-0.375_{a}	0.545
2	386	-0.411_{ab}	0.518
3	10616	-0.395_{a}	0.530
4	3391	-0.395_{ab}	0.531
5	3097	-0.420_{b}	0.525
Total	18776	-0.398	0.530

**Note.* N: number of tweets, Mean: medium sentiment score, SD: Standard Deviation. Means that do not share subscripts differ by $p < .05$ according to Fisher's least square difference (LSD).

The posthoc LSD analysis showed significant differences in sentiment mean scores between Topic 1 and Topic 5 (mean difference = 0.0449479) and between Topic 3 and Topic 5 (mean difference = 0.0255386). These mean differences were statistically significant at the 0.05 level, indicating significantly more negative sentiments in topic 5 compared to topic 1 and 3.

Profile of Mood States

Table 6 displays the frequency of tweets related to different emotional POMS include anger, depression, fatigue, vigour, tension, and confusion in tweets related to chronic pain. Depression had the highest number of tweets with 11,058, expressed in 59% of tweets, followed by confusion expressed in 2,917 (16%) tweets, and anger in 3,540 (19%) tweets. Fatigue and tension categories had fewer tweets with 1,130 (6%) and 1,108 (6%) tweets, respectively. Among all the categories, vigor had the least number of tweets with 921 (5%) tweets.

Comparing POMS with Control Data

The analysis of POMS in the control data (Table 6) highlights differences and similarities in the percentages of mood dimensions in control tweets compared to the chronic pain data. The control data shows percentages for each mood state as follows:: Anger (9%), Depression (56%), Fatigue (3%), Vigour (3%), Tension (5%), and Confusion (13%). In comparison, the chronic pain data demonstrate higher percentages across all mood dimensions, particularly for anger and fatigue, indicating a greater prevalence of anger, depression, fatigue, tension, and confusion within this group.

Table 6

Comparison of Mood States between Control Data and Chronic Pain Data

	Anger	Depression	Fatigue	Vigour	Tension	Confusion
Chronic pain	**19%**	**59%**	**6%**	**5%**	**6%**	**16%**
Control data	9%	56%	3%	3%	5%	13%

POMS by topics

Table 7 presents the percentage distribution of six psychological states across the five topics. The analysis revealed a consistent distribution pattern. Depression emerged as the most prevalent psychological state, accounting for approximately 66.503% of the tweets across all topics. Fatigue followed as the second most prevalent state, with a total percentage of 10.156%. Anger and confusion exhibited similar levels of prevalence, ranging from 10.214% to 7.716% respectively. Tension and vigour showed lower levels of prevalence, with percentages ranging from 4.021% to 1.390%. Regardless of the specific topic, individuals expressed consistent levels of depressive sentiments, with varying degrees of fatigue, anger, confusion, tension, and vigour.

Table 7

Percentage Distribution of Six Psychological States across Five Topics

Topic	Anger	Confusion	Depression	Fatigue	Tension	Vigour
Topic 1	9.565%	7.932%	68.351%	8.787%	4.044%	1.322%
Topic 2	8.290%	8.808%	68.653%	10.104%	2.850%	1.295%
Topic 3	10.277%	7.545%	66.230%	10.635%	3.824%	1.488%
Topic 4	9.997%	7.874%	66.883%	9.466%	4.482%	1.298%
Topic 5	10.752%	7.911%	65.967%	9.848%	4.327%	1.195%
Total	10.214%	7.716%	66.503%	10.156%	4.021%	1.390%

The result also shows some notable differences in the distribution of emotions expressed in tweets across five topics.

Discussion

By utilizing text-mining techniques, namely topic modelling, SA and POMS to analyze 18,778 tweets pertaining to chronic pain, this study aimed to gain insights into the experiences of individuals living with chronic pain by exploring the topics that emerged from their sharing, sentiments and the associated emotions expressed in their tweets. Overall, the topic modelling identified five distinct and meaningful themes encompassing various aspects of chronic pain. Sentiment analysis revealed consistently negative scores across all five topics, which significantly differ from the control data. The POMS shows that depression state was the most prevalent, followed by anger, confusion, fatigue, tension and vigour. Furthermore, the results indicate that these emotions are more extreme in the chronic pain tweets, compared to the control data.

The topic modelling identified five distinct themes that were categorized as follows (1) chronic pain and health, (2) living with chronic pain, (3) temporal aspects of chronic pain, (4) mental impact of chronic pain, (5) medications and drugs for chronic pain. The ICF identified several functioning properties impacted by chronic pain including energy and drive function, sleep function, attention function, emotion, joint function, power function, and exercise tolerance function (Nugraha et al., 2019). The five themes resulting from the topic modelling match fairly well with several of these ICF categories and covered various aspects of life with chronic pain including physical health, mental health, time-related aspect of pain, chronic pain treatment and management, as well as how to live every day with chronic pain. Tighe's research also found Tweet containing the term *"pain"* encompassed a wide range of terms with the most commonly occurring terms including *"feel," "don't," "love," "can't," "ass," "time," "life," "lol," "hurt,"* and *"people"* (Tighe et al., 2015).

The explanation for the themes identified also aligns to some extent with the study conducted by Craig (2003). Craig's research highlights that the experience of pain involves two main components: sensation and affective motivation. Sensation refers to the perception and conscious awareness of the pain sensation, enabling individuals to recognize and feel the pain. Affective motivation relates to the motivation to adjust behaviours to alleviate the pain (Bud Craig, 2003). The identified themes can be associated with different components of Craig's framework, highlighting the experience of pain with the sensation component, focusing on the explicit awareness and perception of pain. Theme "medications and alternative therapies for chronic pain" may correspond to the affective motivation component, reflecting the emotional aspects and the motivation to alleviate pain. The findings also align with previous research by Linton and Shaw, which suggests that persistent pain issues can lead to increased vigilance in emotional responses and avoidance behaviours (Linton & Shaw, 2011). The appearance of emotional words and negative sentiment can be associated with Linton and Shaw's finding on the impact of persistent pain on increasing emotional responses and avoidance behaviours.

Topic 1 indicates that chronic pain experiences involve not only the physical sensations of pain but also interconnected factors such as sleep, mental health, and overall well-being. The health factors associated with the development of chronic pain mentioned in Mills et al. (2019) were pain, multi-morbidity, mental health, medical interventions, weight, sleep disorders and genetics. The word probability in topic 1 reveals the consistency with Mills's research, *"sleep", "weight",* and psychology-related terms *"anxiety",* and *"depression*" are dominant in topic 1. The terms *"rn"* (right now), *"help", and "requesting"* reveal the urgent need to be helped, as reviewed by Eccles & Davies (2021), pain is among the most frequent complaints patients seek for professional healthcare.

Topic 2 highlights living experiences related to chronic pain, including how pain might be affected by various factors or conditions in daily activities. This was also found by Breivik (2006) that chronic pain has a profound effect on the lives of the majority of sufferers, significantly impairing their ability to sleep, exercise, perform daily tasks, engage in social activities, and maintain independence. The theme is aligned with Gereje's study which demonstrated a correlation between chronic pain and psychological distress as well as notable restrictions in daily functioning. The presence of chronic pain was linked to substantial decreases in various measures of overall well-being, with a particular impact on mental health and interference with regular activities (Gureje et al., 1998). As described in the Functioning

Properties (FP) framework of chronic pain assessment and management, FP covers all domains of life which are impacted by chronic pain from leisure and entertainment to performing daily activities, lifting objects, walking, moving around to relationships, remunerative employment and community life (Nugraha et al., 2019).

Topic 3, with the highest marginal probability (43.70%), suggest that most of the tweets revolved around the temporal aspects of chronic pain. Nilsen and Elstad (2009) studied that temporal aspects of pain appear as a central point in numerous studies investigating individuals living with chronic pain. One explanation can be that its chronic and consistent presence causes significant distress for affected individuals. The enduring nature of pain in *"life", "days", "day",* and *"since"* leads to feelings of hopelessness and frustration, as it disrupts daily activities, impairs sleep, and hinders future planning. Temporal terms *"days", "day", year"* were also found in Goudman's study when examing Reddit content related to chronic pain. Pain intermittently disrupted the patients' lives, drawing their focus away from daily activities and impeding their capacity to communicate about their pain (Nilsen & Elstad, 2009). The unpredictable nature of pain episodes induces anxiety and perpetuates a constant state of alertness, which contributes to further distress.

Topic 4 points to the impact on the mental health of people who live with chronic pain. Individuals living with chronic pain frequently encounter psychological and emotional difficulties related to their pain experience (Clark & Cox, 2002). Anxiety, fear, and a pervasive feeling of loss of control contribute to how they experience the pain (Hansen & Streltzer, 2005). The frequent inclusion of terms such as *"depression", "anxiety",* and *"trauma"* reveals the importance of addressing the mental health aspects related to chronic pain. Many studies have been done to prove the occurrence of pain in individuals with depression and the occurrence of depression in patients with pain is more prevalent compared to when each condition is examined separately (Bair et al., 2003; Gambassi, 2009). The prevalence of major depression increased even more significantly with a longer pain history (Cheour et al., 2008). The presence of *"trauma"* can be explained by other studies' findings. For example, there is a higher occurrence of functional somatic syndromes linked to a history of traumatic events (Afari et al., 2014). Another study found a close interrelationship of symptoms observed in both post-traumatic stress disorder (PTSD) and chronic pain syndromes, which supports the notion that these disorders share a reactive nature (Meints & Edwards, 2018). A recent study also observed connections between experiences of childhood trauma, and a history of self-harm in chronic pain patients (McKernan et al., 2019).

Topic 5 highlights the theme related to medication use and the role of opioids in pain management with the high frequency of terms such as "*meds," "opioids," "medication," "opioid," "drugs,"* and *"drug"* . Opioids have been utilized for many centuries as a method to alleviate pain effectively (Yim & Parsa, 2018). Notably, the topic has the most negative sentiment score. It can be attributed to the widespread use of opioids for chronic pain management. However, the use of opioids presents challenges due to the limited understanding and ambiguity surrounding their efficacy (Volkow et al., 2018). This ambiguity arises from their dual nature, where they offer immediate pain relief but also come with undesirable side effects, including tolerance, dependence, and the potential for opioid use disorder. The high prevalence of anger and tension in topic 5 may be attributed to the dysregulation of mood caused by long-term opioid use and the challenges associated with effectively managing chronic pain. Individuals may be expressing dissatisfaction or perceived failures in their medication experiences.

Regarding the SA results, the study observed remarkably similar and predominantly negative sentiment scores across all themes. The mean sentiment scores ranged from -0.375 to -0.420, indicating a consistent prevalence of negative sentiment in tweets related to chronic pain. This finding suggests that individuals expressing their experiences with chronic pain on Twitter commonly convey negative emotions, reflecting the psychological challenges and hardships associated with this condition. To gain a broader perspective, the overall sentiment score was compared to the compound scores of the control data. The comparison revealed significant differences in sentiment between the two datasets. The chronic pain data exhibited a significantly lower mean compound score (-0.3980) compared to the control data (0.1804). These results highlight the distinct emotional expression and sentiment patterns within the chronic pain discourse, emphasizing the unique psychological experiences and struggles faced by individuals living with chronic pain. Combining the five identified themes, these negative sentiment scores suggest that people who live with chronic pain experience mostly negative feelings related to the chronic pain conditions and nature in various areas including daily life, physical health, mental health, and medical treatments.

The POMS finding provided more detailed insights into the emotional experiences of individuals with chronic pain. Depression was by far the most commonly expressed mood state among Twitter users discussing chronic pain. Bair (2003) studied that depressed mood, characterized by negative mood, hopelessness, and despair, significantly affects the pain experience, with an average of 52% of patients living with pain meeting the criteria for depression. It is also noted that the proportion of tweets expressing depression was similarly high in the control tweet. The higher prevalence of emotional distress caused by pain is highly disruptive. It commonly triggers emotions such as anxiety, fear, anger, guilt, frustration, and depression (Linton & Shaw, 2011). Frustration and anger were also among the most expressed mood states suggesting that people with chronic pain are struggling to understand their condition and are experiencing frustration and anger related to their experiences with pain. As explained in Linton & Shaw (2011) anger and frustration can be the result of repeated attempts to find pain relief.

The comparison of mood states between control data and chronic pain data revealed several noteworthy patterns. Both groups show relatively high levels of depression, with the chronic pain group expressing only slightly higher. Interestingly, there was a notably higher percentage of pain-related tweets expressing anger (19%) compared to the control group (9%), indicating the potential emotional impact of chronic pain. Fatigue levels were also elevated in the chronic pain group (6%) versus the control data (3%), reflecting the draining nature of chronic pain. It can be explained because pain and fatigue rank among the most commonly reported symptoms by patients with chronic pain (Eccles & Davies, 2021). These findings highlight the negative influence of chronic pain on mood states, emphasizing the need for targeted interventions and support systems to address the emotional well-being of individuals living with chronic pain.

These findings align with the recommendations put forth by the ICF, which places significant importance on capturing the overall health and lived experience of individuals dealing with chronic pain. Recognizing the multifaceted nature of chronic pain is crucial by considering psychological factors, environmental influences, and behavioural patterns that impact how patients cope with the pain. Additionally, understanding that the effects of chronic pain extend beyond mere symptoms and profoundly affect an individual's daily life and functioning is vital (Nugraha et al., 2019).

Some limitations in using text-mining in general, and specific choices made in this study, should be considered when interpreting the current findings. Firstly, the search term *"#chronicpain"* has the potential to produce a substantial amount of content categorized as "negative" due to the inherent negativity associated with the word *"pain"*. Secondly, to create a reliable Twitter dataset, considerable time is necessary for the process of data cleaning. Spam and commercial contents are inevitable. The data cleaning in this study was performed through several automated and manual steps to remove URLs, duplicates, spam, and commercial content. However, the outcome of such cleaning processes is not flawless. Thirdly, in analysing tweet content, several challenges arise due to the short textual form of tweets and the use of informal language including slang, sarcasm, hashtags, emoticons, and acronyms. To ensure accuracy, A. E. Kim (2013) suggested using trained data collectors for manual coding, ensuring high interrater reliability. However, due to the researcher's limited programming experience, in this study, text mining relied on a pre-existing machine learning algorithm for data analysis, which inevitably lacks specific algorithms and vocabulary tailored specifically for (mental) health-related topics. In the context of the current study, there are also some specific limitations related to the use of Twitter data. Moreover, caution should be exercised when accessing data through the Twitter Streaming API due to its "black box" nature, characterized by a lack of documentation regarding the actual sampling approach (Takats et al., 2022). This means the data might not fully represent all chronic patients, and there could be potential biases in the sampled data. It is also possible that certain groups of users are using Twitter more often than other groups. Regarding the analysis platform, Orange provides researchers with a user-friendly interface supported by convenient widgets to conduct analyses or obtain figures. However, one drawback of Orange is that researchers cannot view or modify the scripts being executed. This limitation may impede the researcher's advanced understanding of the algorithm's workings.

In conclusion, this paper provides readers with a glimpse into the experiences of individuals living with chronic pain through what and how they share about the pain online. This study's findings verified that topic modelling, SA, and POMS analysis on pain-related tweets can provide valuable insights into people’s real-world experiences and offer valuable data for health-related research. For future research, it is recommended to expand the application of big data analysis techniques and explore their applicability to other social media platforms. Taking into advantage of the longitudinal nature of social media data, further long-term study and intervention would enrich our understanding of how chronic pain impacts patients’ life in the long run. Refining the dictionaries would contribute to in-depth automated content analysis for chronic pain context. Building dictionaries for mental health content analysis is a challenging task, I leave such efforts for future research.

The paper brings attention to the adversity endured by those grappling with chronic pain. This understanding improves health care support through pain management strategies, psycho-education, and self-help tools, empowering individuals to effectively cope with the pain, and to lead fulfilling lives without being constrained by their chronic condition when making future plans.

Appendix

List of Removed Accounts

The New York Times, National Geographic, CNN International, UberFacts, TIMES NOW, NPR, New Scientist, Los Angeles Times, The Independent, Newsweek, CBC News, The Telegraph, Daily Mail Online, NowThis, AFP News Agency, World and Science, FORTUNE, BBC Health News, European Commission, Harvard University, Psychology Today, Daily Mail U.K., The Irish Times, CBC, National Geographic Magazine, Johns Hopkins Medicine, Everyday Health, Harvard, Medical Xpress, US Association for the Study of Pain, etc.

List of stopwords

1, 2, 3, 4, 5, 6, 7, also, actually, bc, due, Etc, etc, ever, get, im, i've, W, w, That’s, that's, might, Via, via, like, Lot, Could, one, others, person, people, Two, two, %,*, @, #pain, #chronicpain, Yes, yes, u, Us, us, Many, Like, I’m, i'm, dr, would, may

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