Sharing the pain: an observational analysis of Twitter and pain in Ireland

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ABSTRACT

Introduction Studies involving Twitter and chronic pain can provide highly valuable patient-generated information. The aim of this paper was to examine pain-related tweets in Ireland over a 2-week period from 22 June 2017 to 5 July 2017 using pain-related keywords. We wished to identify Twitter user gender profile; most common discussion topics; sentiment analysis; and dissemination of tweets.

Methods A third-party data analytics company conducted a Twitter social media analysis over a randomly chosen 14-day period between the dates 22 June 2017 and 5 July 2017. All relevant keywords were included in the search. Author group consensus yielded 24 terms. Geographical location was restricted to Ireland. A computational sentiment dictionary was used to provide a rating of the emotional properties of the text on a 9-point scale from −5 to +4 of negative to positive sentiment. Dissemination was calculated by the number of times the tweet was displayed (‘impressions’).

Results There were 941 tweets identified during the study from 715 contributors. These generated 2.88 million impressions. The most frequently occurring keywords were headache (n=321); migraine (n=147); back pain (n=123); cannabis (n=114); and chronic pain (n=85). Three were 1.94 times as many tweets from females as males. The highest proportion of tweets from female users was in the fibromyalgia (83%) and migraine (60%) categories; and from males in the sciatica (35%), chronic pain (34%) and back pain (32%) categories. Cannabis-related tweets reflected mostly non-personal content (90%), with a highly positive sentiment, and the highest number of impressions per tweet. The largest amount of advice was offered in the back pain category.

Conclusion A substantial discussion of pain-related topics took place on Twitter during our study period. This provided real-time, dynamic information from individuals on discussion topics in pain medicine. This can be used to gain a greater understanding of the pain experience. As patients are increasingly acquiring healthcare information through online sources, high-quality information from approved sources should be promoted on such platforms.

INTRODUCTION

Patients are increasingly using internet-based forms of healthcare. These include internet-delivered interventions and health information accessed through online patient forums and social media websites, such as Facebook, YouTube, and Twitter. Internet-delivered psychological interventions in chronic pain have been demonstrated to be effective. Such models of healthcare provision are particularly attractive in areas where long waiting lists exist such as in chronic pain. Waiting times for chronic pain clinics in excess of 6 months are medically unacceptable and result in significant deterioration in the clinical status of people with chronic pain (PWCP).

Twitter is a social media platform where users post ‘microblogs’ or ‘tweets’ with a maximum of 280 characters. Many individuals use Twitter for sharing thoughts and feelings, personal anecdotes, or commenting on topical items. Some users use social media to comment on medical experiences or symptoms. Infodemiology involves the use of electronic information, such as social media platforms, for the real-time study of disease characteristics and patterns. Infodemiology has been conducted on Twitter to retrieve data in a multitude of areas, such as smoking, prescription drug abuse, diet, dental pain, mood, and chronic pain.

Studies involving Twitter and chronic pain can provide highly valuable patient-generated information, which is authentic and collected in real time. This bypasses traditional problems encountered with retrospective collection methods, such as recall bias. PWCP have reported enhanced psychological, social, and cognitive outcomes from social media use.

The aim of this paper was to examine pain-related tweets in Ireland over a 2-week period between the dates 22 June 2017 and 5 July 2017 using pain-related keywords. We wished to identify:

1. Twitter user gender profile.
2. Most commonly used pain-related keywords and phrases.
3. Sentiment analysis of tweets.
4. Reach of pain-related tweets.

METHODS

A third-party data analytics company (Olytico, Dublin, Ireland) was used to collect data for this study. Olytico has a license to access the Twitter Firehose, which provides access to the complete stream of public messages generated on Twitter. This enabled us to search for pain-related tweets using defined pain-related keywords. Social network analysis was limited to Twitter and geographical location restricted to Ireland. Data were collected over a randomly selected 14-day period from tweets between the dates 22 June and 5 July 2017.
This timeframe was not chosen to coincide with any particular event or conference.

Twenty-four keywords and phrases were identified through author group consensus based on pain Medical Subject Headings terms and other suggested common pain discussion topics. All relevant keywords were included in the search. There was no established method from prior studies for selecting these terms. The chosen terms were chronic pain; acute pain; back pain; pain clinic; Irish Pain Society; nerve pain; muscle pain; sciatica; fibromyalgia; carpal tunnel syndrome; headache; migraine; trigeminal neuralgia; slipped disc; neuropathy; myofascial; neuropathic pain; medical cannabis/cannabis/marijuana/endocannabinoids; post-herpetic neuralgia; joint pain; cancer pain; back spasm; neck pain; and Chronic Pain Ireland.

The search output from our analysis included author name; text of tweet; time and date of tweet; type of tweet (regular; retweet; or reply); impressions generated; and location of author. A regular tweet was an authentic tweet from the Twitter user; a retweet was a reposted tweet from another user; and a reply was a public response to another user’s tweet. The search output did not reveal the Twitter user gender profile; therefore, authors were manually searched for on Twitter to identify this based on the biographical details displayed on the account. Where this was not shown or where the user represented an organization, gender was classified as ‘not available’. This was performed by two independent researchers and results were compared with ensure accuracy. Once this analysis was conducted, usernames were deleted from our data set.

The text of collected tweets formed the basis of our analysis. The most commonly occurring keywords and phrases were identified from our data set by filtering for these terms. The same terms and other suggested common pain discussion topics were manually searched for on Twitter to identify this based on the biographical details displayed on the account. Where this was not shown or where the user represented an organization, gender was classified as ‘not available’. This was performed by two independent researchers and results were compared with ensure accuracy. Once this analysis was conducted, usernames were deleted from our data set.

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The text of collected tweets formed the basis of our analysis. The most commonly occurring keywords and phrases were identified from our data set by filtering for these terms. The same keywords occurring twice within one tweet was counted once. However, separate keywords occurring in the same tweet were counted in separate lists. Tweets were manually analyzed to determine whether they related to oneself (‘personal tweets’), or other topics (‘non-personal tweets’). This analysis was conducted by two independent researchers who categorized the tweets and compared results for accuracy.

Original research

| Topic | Category | Tweet |
|-------|----------|-------|
| Headache (n=321) | Personal | My skull wanted to explode with the headache i had earlier |
| | Personal | Woke up this morning with the biggest headache and cuts and bruises everywhere, what was I at last night |
| Migraine (n=147) | Advice | #Acupuncture better than usual care for #musculoskeletal conditions, knee #osteoarthritis and chronic #headache |
| | Research | Many suffer w/ a migraine…more abt breakthrough research & treatment today in new series by @** @** |
| | Personal | i can sense a really bad migraine coming on and i can’t even do anything to stop it because i forgot to pick up my prescription https://** |
| | Advice | Blurred vision? Flashes of light? You could be suffering THIS migraine with no headache https://** |
| Back pain (n=117) | Research | Some medications dont help back pain as much as we thought https://** @** #HarvardHealth |
| Chronic pain (n=97) | Awareness | Is Back Pain Hurting Your Career? - https://** |
| Cannabis’ or ‘Marijuana’ (n=113) | Advice | With medical cannabis you could reduce or replace you opioid medications but not in Ireland at least not yet #MIM…https://** |
| | Personal | Knowing that medical cannabis oil can legit cure my medical condition but the government won’t make it legal over here pisses me of so much |
| | Awareness | Vera Twomey announces Ava will start medical cannabis treatment tomorrow - in Holland https://** |
| Fibromyalgia (n=35) | Awareness | How this men-only support group helps sufferers struggling with chronic pain and stigma https://** |
| | Awareness | I’ve just come across this fantastic artist who does a pictorial diary of her struggle with chronic pain. This… https://** |
| | Advice | Try cbdoil mate… my wife uses it for chronic pain and helps. |
| Pain ‘other’ (n=57) | Advice | #yoga is many many benefits, one of which is assisting with the management of pain….so why not join one of our…https://** |
| | Advice | People Go Crazy For This Recipe! It Heals Knee, Bone and Joint Pain https://** |
| | Awareness | Well deserved lunchbreak for data collectors @** during the national prevalence study on cancer pain and constipation. @** https://** |
| Sciatica (n=23) | Personal | I don’t want to have fibromyalgia :I don’t wanna be in pain anymore. |
| | Awareness | Now on Audible! Fibromyalgia: My Personal Experiences https://** via @** #fibro #chronicpain |
| | Awareness | Morgan Freeman uses marijuana to treat his #chronicpain from #fibromyalgia. https://** |

@***, reply to [name deleted]; # (hashtag) identifies messages on a certain topic on Twitter; https://**, hypertext transfer protocol secure [website address deleted]; w/a, with a; abt, about; # (hashtag) identifies messages on a certain topic on Twitter; @**, reply to (name deleted); abt, about; https://**, hypertext transfer protocol secure (website address deleted); w/a, with a.
were defined as reflecting the direct impact of a symptom or disease on people, whereas non-personal tweets were news or information related.\textsuperscript{13} Non-personal tweets were further categorized into ‘raising awareness’, ‘offering advice’, and ‘medical research’. Where a term was used outside of the context of a pain complaint and instead used in a metaphorical sense, these tweets were excluded from our analysis (eg, ‘selection headache for Gatland’).

Tweets were analyzed for sentiment. Sentiment analysis is an estimation of the emotional properties embodied in the text. This was performed using a computational method that employs a sentiment dictionary. This contains measures of pleasure and arousal for 10,680 English words, which when combined produces an overall sentiment rating.\textsuperscript{14} These words are rated on a 9-point scale from −5 to +4 of negative to positive sentiment. Tweets with two or more recognizable words can produce an overall sentiment rating for the tweet.

Dissemination of tweet content was calculated using the number of ‘impressions’ generated. This tells us how many Twitter accounts the tweets were delivered to and gives an indication of how large the potential audience for the tweet was. Statistical analysis was performed using Statistical Package for Social Sciences (SPSS) software version 26.\textsuperscript{15} For normally distributed continuous variables (eg, sentiment analysis), the t-test was used to compare two groups (eg, gender) and analysis of variance used to compare more than two variables (eg, keyword categories).

RESULTS
There were 941 tweets identified during the study from 715 contributors. This included 493 original tweets (52%), 319 retweets (34%), and 129 replies (14%). These reached 2.62 million accounts and generated 2.88 million impressions.

Tweets by category
The most frequently occurring keywords were headache (n=321); migraine (n=147); back pain (n=123); cannabis (n=114); chronic pain (n=85); pain ‘other than back pain or chronic pain’ (n=57); fibromyalgia (n=34); and sciatica (n=23). Table 1 shows the most commonly occurring topics and a random sample of tweets from each topic.

Tweets by gender
Gender could be identified by biographical details on account information in 75% of tweets (708/941). The remaining 25% of tweets were either from accounts where gender was not disclosed, or from an organization. There were 1.94 times as many tweets from females as males. The highest proportion of tweets from female users was in the fibromyalgia (83%) and migraine (60%) categories, while the lowest was in the cannabis category (39%) (figure 1). The highest proportion of male tweeters was in the sciatica (35%), chronic pain (34%) and back pain (32%) categories, while the lowest was in the fibromyalgia category (11%). The highest proportion of individuals who did not identify their gender or represented an organization (‘gender N/A’) was in the cannabis category (34%), and the lowest was in the fibromyalgia category (6%).

Personal and non-personal tweets
Personal tweets represented 52.5% of tweets (495/941). The highest proportion was in the headache (90%) and migraine (66%) categories, while the highest proportion of non-personal tweets was in the cannabis (90%) category (figure 2). Non-personal tweets were aimed at generating awareness (49.2%), offering advice (28.4%), or promoting medical research (18.8%) (figure 3). Cannabis had by far the largest number of tweets aimed at generating awareness (n=99). There was a high proportion of tweets offering advice in the headache, back pain, and pain ‘other’ categories.

Reach
While headache was the most common keyword, with more than double the incidence of its closest competitor, migraine still generated more impressions (618 237) compared with headache (607 473) (figure 4). Cannabis was a close third, despite having significantly fewer keyword incidences (573 671). Back pain was the outlier with significantly fewer impressions than those beside it in the keyword table. This indicates a broad reach for headache, migraine and cannabis on Twitter.

Sentiment analysis
There were 768 tweets with two or more recognizable terms, which allowed for an estimate of their sentiment. This represented 641 tweets and 127 retweets. The mean sentiment of all tweets was −0.17±0.88; 52.5% of tweets were negative overall. There was no sentiment disparity between the sexes (95% CI −0.1692 to 0.1662; p=0.98). Retweets were significantly more likely to reflect a positive sentiment (95% CI 0.0817 to 0.4089; p=0.0034). Figure 5 contains a boxplot of sentiment of tweets by topic category. The most positive sentiment was in the cannabis and fibromyalgia categories, where 83% and 68% contained an overall positive sentiment respectively.
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DISCUSSION
Twitter provides a platform for generation of real-time, unsolicited information that can provide insights into patterns and traits of many diseases in a real-world setting. Human memory is subject to recall bias; we cannot recall everything we experience and memories of experiences fade over time. Memory is selectively encoded and is influenced by factors such as emotions, duration of events, and intensity of experience. We typically remember the ‘peak’ intensity of the pain and also how we felt at the ‘end’ of the pain; this is described as the ‘peak-end effect’. This can affect recall of experiences that are repetitive over time, such as pain symptoms in chronic pain conditions. Depressed patients suffering from chronic pain are subject to cognitive distortions. This implication means that retrospective reports of pain are likely to be inaccurate. Real-time collection of social media health-related data can enhance our understanding of chronic diseases and provide a self-expressed, unfiltered, and possibly more accurate account of pain symptoms.

Social media use has been associated with improved social, psychological, and cognitive outcomes in chronic pain. Most people tend to be passive users of social media and read content rather than actively posting. Active engagement is associated with better emotional outcomes. The most common users of social media in chronic pain are well-educated females, in relationships, aged 30–60 years. In our study, 64% of those who disclosed their gender were female users. This figure rose to 70% when only tweets of personal pain symptoms were included. The highest proportion of female Twitter users was in the fibromyalgia category (83%), followed by migraine (60%) and headache (50%) (figure 3). Fibromyalgia has been shown to be the most common underlying chronic disease among social media users with chronic pain.

The most common pain-related keyword found in tweets was ‘headache’ appearing in 34% of all tweets (n=321). Tweets containing the keyword ‘headache’ alluded to both physical and non-physical complaints. The words ‘pain’ and ‘headache’ are used outside of medical parlance for everyday topics and therefore can reflect a variety of themes outside of physical pain. Migraine was the most common topic outside of ‘headache’, present in 15.6% of tweets. While those tweeting about migraine may not have a formal diagnosis of migraine, it has been shown that those who report their headache symptoms as migraine are three times more likely to legitimately suffer from this. The majority of tweets related to headache (90.3%) and migraine (66%) were generated from patients’ report of ongoing symptoms. The majority of tweets had a predominantly negative sentiment, which is unsurprising.

Advice on Twitter
Advice surrounding back pain and headache made up a significant proportion of these categories. Patients are increasingly sharing their personal medical experiences online; the majority of online material on scientific forums is predominantly based on opinions and personal experience, rather than on scientific results. In the USA, 41% of e-patients have read other patients’ personal medical stories on an online blog or website and 40% of Americans doubt their doctor’s professional opinion when it conflicts with online information from social media websites. Users of health services, particularly those who are on long waiting lists to access health services, can be vulnerable to misleading information. As healthcare professionals, we should advise caution on the content of healthcare information that is promoted on social media platforms. Patients accessing material online may not have the expertise to filter material that is not scientifically rigorous. This can have a negative impact, as demonstrated by the adverse effect of online parents’ discussion forums on the uptake of childhood vaccination. Furthermore, the quality of retrieved material is dependent on the search terminology. As patients actively search for online material themselves, material may not be searched for in a wholly objective manner and may be subject to confirmation bias. A systematic review found that while high-quality material produced by government and professional organizations is accessible on YouTube, there also exists poor-quality information, primarily anecdotal, which online users have a high likelihood of coming into contact with. In light of this, it is important that high-quality health information from

Figure 3  Content breakdown of non-personal tweets by topic.

Figure 4  Reach of tweets by topic.

Figure 5  Sentiment analysis by topic.
approved sources be promoted on these platforms to ensure vulnerable individuals are not exploited by misleading advice or information.

Medical cannabis and Twitter

‘Cannabis’ tweets had a unique set of characteristics compared with the other categories. They were mostly ‘non-personal’ (97%), awareness promoting (88%), with a highly positive sentiment (83%), and the greatest reach per tweet. They also had the highest proportion of users who represented an organization. The reasons these figures could differ are manifold. First of all, cannabis use is highly restricted in the Republic of Ireland and is not available for chronic pain conditions according to the Health Products Regulatory Agency (HPRA) recommendations on the use of cannabis products for medical use in Ireland. This is at odds with the European Pain Federation (EFIC) position paper on the use of cannabis products in chronic pain conditions. It also differs from the other categories in our study, in that it is a form of treatment rather than a symptom or a diagnosis. Therefore, individuals are unlikely to be tweeting about their use of medical cannabis in Ireland for chronic pain conditions.

Medical cannabis is evidently a controversial topic, as demonstrated by the conflicting statements from the HPRA and EFIC. Accordingly, this topic generated the highest number of impressions per tweet. While sentiment analysis was mostly positive for cannabis-related tweets, it is difficult to comment on how these data reflect public opinion without comparing it to other data points such as survey data of the public on this topic. There appears to be a disparity between public perception of efficacy and safety of cannabis-related products and the reality. It is quite likely that this positive attitude represents a vocal minority of the population who are eager to champion a cause that is important to them. Public opinion has evolved to incorporate multiple complex and interwoven public domains including Twitter and other social media platforms. This can lead to distortion of public discourse. Further work needs to be done to ascertain whether social media data on these issues actually reflect an opinion that is held by the wider society.

Concerns about social media

Other concerns exist regarding social media use among patients including regulation of privacy of data, doctor–patient confidentiality, and loss of control over information provided to patients. Some of these concerns can be addressed and require engagement on the part of physicians. It is essential that healthcare professionals provide leadership in this area by facilitating access to reliable, scientifically valid online information, and through the development of best practice guidelines for accessing information for patients. The development of social media guidelines for healthcare professionals and incorporation into medical student education is essential to ensure optimal integration of novel media platforms into modern medicine. Novel approaches are needed to support a symbiosis between patients and physicians on social media. Physicians and public health specialists need to adapt to the new ways in which patients consume information. Many patients are rating their healthcare experiences online. Insights gained from social media posting from patient populations can be used by physicians to gain a valuable perspective on their patients’ worldview. Adapting to patients’ behavior can result in greater patient engagement, patient satisfaction, quality of care, and improved health outcomes. This can enrich the doctor–patient therapeutic relationship.

Limitations

This study was conducted over a 2-week study period. Public discourse on social media can change rapidly and is dictated by world events. Findings may be distorted by events that were topical during this timeframe. The 2-week study period was chosen at random and not timed with any particular events or conferences. Ideally, this study should be replicated over a longer timeframe to establish the consistency of our findings. Furthermore, the geographical location of tweets was restricted to Ireland. It is unclear whether the pattern of Twitter use described here is comparable internationally.

While social media analysis provides a data set of raw and unfiltered material, it is difficult to determine if the pain narratives expressed on this forum are representative of narratives that exist broadly within these communities. Tweets exist within a public sphere where they can interact with interconnected ideas and information; words and phrases can be linked to a specific topic or theme via ‘hashtags’ and opinions expressed in tweets can be replies or retweets, which lead to an increased dissemination of similar content. Often, certain views can appear more mainstream than they actually are. This can result to an ‘echo chamber’ phenomenon, whereby certain opinions and perspectives are reinforced and other viewpoints may be under-represented. It is also possible that these views being promoted on social media could represent an underlying specific agenda. Promotional activities have begun to play a large role in social media discourse. The Cambridge Analytica hearings demonstrated that data can be used to strategically manipulate and to deceive public opinion. This has important implications for online narrative communities such as Twitter. Views within these forums should therefore be interpreted with caution.

Our analysis provided an insight into common pain-related discussion themes on social media and included assessment of the emotional content, however further text mining could be performed in order to determine if additional patterns or trends exist within identified categories. For example, source and dissemination of non-personal content, such as advice, could be explored to determine the reach of evidence-based content from reputable sources. This could provide opportunities for development of social media strategies for the promulgation of high-quality content. Factors that influence retweet probability could be investigated or individual categories could be analyzed over a longer period of time (eg, fibromyalgia) to determine if new knowledge or patterns can be gleaned from these groups.

Assessment of sentiment was performed using a computational sentiment dictionary. Other computational methods of sentiment analysis exist including machine learning algorithms such as naïve Bayesian networks, support vector and maximum entropy analysis. These approaches require sufficient high-quality text to enable proper natural language analysis and therefore may not be suitable for analysis of short segments of text in tweets. While sentiment dictionaries may provide a more suitable alternative, questions remain over the validity and reliability of such data, particularly within the context of a 280-character limit which may contain abbreviations, slang, and ‘smilies’. Verification of sentiment analysis using a common sense reasoning approach was not performed by the authors. Comparison of sentiment should ideally be undertaken with other data points, such as survey data, to confirm accuracy of results.

CONCLUSION

An extensive discussion of pain-related topics took place on Twitter during our study period. This provided real-time,
dynamic information from individuals on discussion topics in pain medicine. This can be used to gain a greater understanding of the pain experience. As patients are increasingly acquiring healthcare information through online sources, high-quality information from approved sources needs to be promoted on such platforms. Novel approaches are required to ensure satisfactory adoption of social media into mainstream medicine.

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**REFERENCES**

1. Merelli M, Gray K, Martin-Sanchez F, et al. Patient-Reported outcomes and therapeutic affordances of social media: findings from a global online survey of people with chronic pain. *J Med Internet Res* 2015;17:e20.

2. Buhrman M, Skoglund A, Husell J, et al. Guided internet-delivered acceptance and commitment therapy for chronic pain patients: a randomized controlled trial. *Behav Res Ther* 2013;51:307–15.

3. Lynch ME, Campbell F, Clark AJ, et al. A systematic review of the effect of waiting for treatment for chronic pain. *Pain* 2008;136:97–116.

4. Dear BF, Titov N, Perry KN, et al. The pain course: a randomised controlled trial of a clinician-guided internet-delivered cognitive behaviour therapy program for managing chronic pain and emotional well-being. *Pain* 2013;154:942–50.

5. Eysenbach G. Infodemiology and infoveillance: framework for an emerging set of funding agency in the public, commercial or not-for-profit sectors.

6. Merolli M, Gray K, Martin-Sanchez F, et al. Guided internet-delivered acceptance and commitment therapy for chronic pain patients: a randomized controlled trial. *Behav Res Ther* 2013;51:307–15.

7. Lynch ME, Campbell F, Clark AJ, et al. A systematic review of the effect of waiting for treatment for chronic pain. *Pain* 2008;136:97–116.

8. Dear BF, Titov N, Perry KN, et al. The pain course: a randomised controlled trial of a clinician-guided internet-delivered cognitive behaviour therapy program for managing chronic pain and emotional well-being. *Pain* 2013;154:942–50.

9. Eysenbach G. Infodemiology and infoveillance: framework for an emerging set of funding agency in the public, commercial or not-for-profit sectors.

10. Mullins CF, et al. Reg Anesth Pain Med 2020;45:597–602. doi:10.1136/ramp-2020-101547