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Tweeting back: Predicting new cases of back pain with mass social media data

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ABSTRACT

Back pain is a global health problem. Recent research has shown that risk factors that are proximal to the onset of back pain might be important targets for preventive strategies. Rapid communication through social media might be useful to deliver timely interventions that target proximal risk factors. Identifying individuals who are likely to report back pain via Twitter could provide useful information to guide online interventions. In a sample of 742,028 back pain tweets, we applied a case-crossover design to quantify the risks associated with a new tweet about back pain. The odds of tweeting about back pain just after tweeting about selected physical, psychological, and general health factors were 1.83 (95% CI = 1.80 - 1.85); 1.85 (95% CI = 1.83 - 1.88); and 1.29 (95% CI = 1.27 - 1.30), respectively. These findings give directions for future research in utilizing social media for innovative public health interventions.

INTRODUCTION:

Back pain is a major public health problem and the leading cause of disability worldwide.[1] The societal burden of back pain is enormous - annual direct costs of treating back pain are approximately $86 billion in the US,[2] and indirect costs through lost productivity take the burden well past $114 billion.[3]

Risk factors such as age, low educational status, and occupational demands are associated with the development of back pain.[4] However, some of these factors are difficult to modify. Evidence also suggests that preventive strategies that target modifiable risk factors such as workplace interventions have not been successful in reducing this burden.[5] Risk factors that are more proximal to the onset of back pain are likely to play a critical role, as approximately 80% of patients who experience a new episode of back pain report a sudden onset.[6] A recent study showed that exposure to proximal risk factors, for example, manual tasks that involve heavy loads, or being fatigued, increased the likelihood of the onset of back pain.[7] The authors concluded that proximal risk factors might be suitable targets for interventions aimed to reduce the incidence of low back pain. However, for proximal risk factors, the timespan between exposure and the onset of back pain is brief. New strategies that can reach individuals in a timely manner may offer new directions for public health interventions.

Social media platforms such as Twitter enable rapid communication to mass populations via cost-effective methods. Every day there are approximately 100 million active Twitter users who send short messages called ‘tweets’ to a wide-reaching worldwide audience.[8] Many people share their health status via social media [9–11] and the potential for use of these data has been recognized, first by descriptive accounts of what people report,[12] and then by sophisticated analyses mapping the spread of infectious diseases such as influenza.[9,13] Given the high prevalence of back pain in the community, it is unsurprising that people report their back pain through social media.[10] Early identification of individuals who are likely to report back pain via social media could provide useful information to guide online public health interventions. We used an epidemiological design (case-crossover) to investigate whether tweets about potential risk factors can predict users' tweets about their back pain.

METHODS:

The University of South Australia Ethics Committee approved this study.

Sample

From all active users of Twitter worldwide in the two-year period 2010-12, we identified 'case-tweets': those that contained a phrase, in English, that related to back pain (*painful back, pain in my back, sore back, hurt my back, I've got backache, injured my back, buggered my back, my back is killing me, I've got back pain, put my back out, my back hurts, back started hurting*). Those who tweeted about back pain, but had not tweeted about back pain in the previous 3 months, were included in the study. We modified the de Vet definition for acute back pain,[15] where a single tweet about back pain preceded by 3 months without a back pain tweet was defined as a new episode of back pain. Those with ongoing back pain (more than one tweet about back pain within a 3 month period), or tweeting about back pain in a language other than English, were excluded. No limits were placed on age.

Design

We used a retrospective case-crossover design. Case-crossover studies are suited to identifying proximal risk factors that immediately precede the onset of a condition or injury (in this study, a new tweet about back pain). Essentially, it is used to answer the question “was the event/injury triggered by something unusual that happened just before?”.[16] This self-matching method where the participants act as their own control means that estimates are adjusted for confounders (e.g. age, gender, number of previous episodes) by design.[17] Controlling for these confounders gives an advantage to case-crossover designs over traditional case-control designs for studying transient risk factors. This has been exemplified in the study of conditions such as, myocardial infarction[18] and occupational hand injuries.[19]

We specified a ‘hazard period’ - the 48-hour window that preceded each case-tweet; and two ‘control periods’ of 48-hours each - one that preceded the case-tweet by 2-weeks and one that preceded it by 2-months (Figure 1). By limiting our inclusion criteria to individuals with one back pain complaint over a 3-month period, we established two control periods where individuals did not tweet about back pain. Within the hazard and control periods, we searched for ‘risk-tweets’ that were predefined physical, psychological, or general health phrases that represented possible risk factors for back pain. Our aim was to utilize a comprehensive group of risk-terms to pick-up tweets that represent three broad underlying constructs: risky physical behaviour, negative psychology, and poor general health. These domains reflect existing theories that incorporate factors from physical, psychological, and biological determinants of pain.[20] We used the following terms to detect exposure to physical factors: *gym, lifting, lifted, lift, bending, bent, went for a run, jogging, went for a jog, went running, training for a half marathon, training for a marathon, doing weights, treadmill, aerobics, stepercise, dancing, power walking, on the crosstrainer, yoga, pilates, throwing, bowling, played golf, kicked a footie, played soccer/squash/tennis*; psychological factors: *depressed, stressed, bad mood, feeling down, angry, tired, exhausted, washed out, anxious, fed-up*; and general health factors: *sick, ill, flu, crook, cold, got drunk/tanked/hammered/pissed, under the* *weather, shattered, not sleeping*. This list of potential risk factors was derived by an expert group of researchers and clinicians in the field of back pain. The aim was to create a comprehensive list of possible risks that have been implicated in triggering a new back pain episode. This process was guided by existing evidence on proximal triggers and clinical expertise. The content was checked by an independent group of researchers and additional terms were added.

We measured the frequency of physical, psychological, and general health risk tweets during the hazard and two control periods for each case tweet. From this we generated the frequencies of discordant pairs. “Hazard discordant pairs” were the number of individuals who tweeted the risk during the hazard period but not the control period; and “control discordant pairs” were the number of those who tweeted the risk during the control period but not the hazard period.

Analysis

We compared the exposure (presence of risk tweets) in the 48-hour period immediately before the case tweet (hazard period) with the 48-hour control period that was 2-weeks before the case tweet (control period). We also made the same comparison using the 2-month control period. We used multiple conditional logistic regression to calculate independent odds ratios and 95% confidence intervals for physical, psychological, and general health risk tweets. Analyses were conducted using the ‘*clogit’* command in STATA 13 software (StataCorp. 2013. Stata Statistical Software: Release 13. College Station, TX: StataCorp LP). Because odds ratios can inflate small changes in probabilities, we conducted alternative analyses to estimate positive predictive values (PPVs). The PPVs were calculated as the proportion of individuals who tweeted the risk during the hazard period and tweeted about back pain (frequency of true positive/frequency of positive risk).

RESULTS:

Over 2 years, 742,028 'case-tweets' were identified. In the case tweets, individuals sent a public tweet that contained a phrase, in English, that related to back pain, and had not tweeted about another back pain episode in the previous 3 months. From the total sample, 219,694 were female, 126,052 were male, and 396,282 did not disclose their gender.

Figure 1 depicts the two types of discordant pairs: the 'hazard discordant pair' where the individual tweets a risk factor in the hazard period (48 hour period before tweeting about back pain) but not in the control period (48 hour period that is either 2 weeks or 2 months prior the case tweet); and the 'control discordant pair' where the individual tweets a risk factor in the control period, but not in the hazard period. Figure 2 presents the frequencies of these discordant pairs for each domain of risk tweet (physical, psychological, and general health). We observed higher frequencies of hazard discordant pairs than control discordant pairs for all risk tweet domains. This shows that there were more individuals who tweeted a risk factor immediately prior to a back pain tweet, than people who tweeted a risk factor that was not followed by a back pain tweet. This trend was observed in both control comparisons at 2 weeks and 2 months.

In Table 1, we present the odds ratios and PPVs for each risk tweet for the two control comparisons (2 week and 2 month). The odds ratios represent the odds of tweeting the risk factor prior to a back pain tweet compared to the odds of tweeting the risk factor when it is not followed by a back pain tweet. Psychological tweets showed the highest odds, followed by physical, then general health tweets in the 2-week control comparison. A similar trend was observed for the 2-month control comparison. The odds in the 2-month control comparison were greater than the odds observed in the 2-week control comparisons. This trend was more pronounced for psychological and physical risk tweets. The PPVs represent the likely risk that an individual will tweet about back pain, if they tweet a given risk factor. The PPVs follow a similar trend to the odds ratios. For the 2-week comparison, psychological tweets were associated with the highest risk of a subsequent tweet about back pain, followed by physical, then general health tweets. For the 2-month comparison, psychological and physical tweets showed similar risks, followed by general health tweets.

Table 1. Odds ratios, PPVs and their 95% confidence intervals for physical, psychological, and general health risk tweets

Control period	Risk tweet	Hazard discordant pairs[a]	Control discordant pairs[b]	Odds ratio (95% CI)	PPV% (95% CI)
2 week	Physical	64 618	48 366	1.30 (1.28 - 1.31)	55.71 (55.45 - 55.97)
	Psychological	73 646	54 072	1.33 (1.31 - 1.34)	56.03 (55.79 - 56.27)
	General health	41 082	32 296	1.22 (1.20 - 1.23)	54.55 (54.23 - 54.86)
2 month	Physical	70 356	35 358	1.83 (1.80 - 1.85)	64.17 (63.90 - 64.44)
	Psychological	80 006	39 937	1.85 (1.83 - 1.88)	64.14 (63.89 - 64.39)
	General health	45 816	30 757	1.29 (1.27 - 1.30)	58.34 (58.02 - 58.66)

[a]Frequency of those who tweeted the risk during the hazard period but not the control period.
[b]Frequency of those who tweeted the risk during the control period but not the hazard period.
PPV = positive predictive value

DISCUSSION:

In this case-crossover study we used a large database of archived tweets from 742,028 individuals and found antecedent tweets about psychological, physical and general health factors increased the odds of a new tweet about back pain. Our alternative analyses of PPVs showed similar trends to the odds ratios. Although the advantage of the PPV is that it provides an easily interpretable estimate of the predictive value of each risk-tweet, the PPVs should be interpreted with caution because they do not take into consideration the matched-pairs of the case-crossover design.

Recent research has shown that modifiable proximal risk factors such as manual tasks involving awkward positioning or being fatigued were associated with higher risk for the onset of back pain.[7] The terms we used to identify physical and psychological risk factors mirrored the key proximal risk factors identified by Steffens et al., for example, “lifting”, “tired”, and “exhausted”. We found higher odds for psychological factors than we did for physical factors. This might be due to the fact that people are more likely to tweet about their psychological state, than about ongoing physical activities (such as lifting) . It is also possible that psychological symptoms aggregate a range of negative sentiments [21] and last longer than physical or general health factors. Although this might have increased the point-frequencies of psychological tweets and inflated the number of concordant pairs, this does not influence the odds ratios because they are derived from discordant pairs. Thus, the case-crossover design protects against this source of bias.

Only a few studies have investigated pain-related tweets, all of which have been descriptive content analyses.[10,21,22] Our study extends the findings of these studies by applying a well-established epidemiological design to identify proximal risk tweets that predict tweets about back pain. By using the case-crossover design, the effect of confounding is minimised because participants are self-matched. We also limit recall bias, a fundamental problem to most traditional retrospective case-crossover studies,[23] by using an archive of unsolicited self-report tweets.

There are some limitations if one attempts to generalize our findings to real cases of back pain. Those who report back pain via Twitter in an unsolicited manner may not truly reflect back pain cases studied in traditional studies. Data that dispel that possibility is not yet available for back pain tweets. In other fields such as HIV research, validation work has shown that databases of tweets about HIV represent geographically defined databases of real cases.[24] Similar work in the back pain field would improve our understanding about the feasibility and validity of using social media data to generalize our findings to real back pain cases. It is also possible that Twitter users may not truly represent the general population who experience back pain. This limits the generalizability of our findings. We recognize that our risk-terms for possible triggers may not be exhaustive, and that this might have introduced bias and underestimated the effects. Future work in this area could evaluate the predictive sensitivity and specificity of individual risk factors. Reverse causality (i.e. back pain tweets causing risk tweets) is also another issue that warrants further investigation. In this study, it is plausible that prior episodes of back pain may have influenced the frequencies of the observed risk tweets.

In other areas of healthcare, epidemiologists have called for innovative approaches that use online social media to deliver preventive health interventions.[25–28] Recent meta-analyses have also shown that behavioural interventions delivered through social media have positive effects on health outcomes.[29] For the prevention of back pain, informatics based interventions could utilize real-time surveillance methods to identify ‘at risk’ individuals, then direct online educational material [30] to improve awareness and modify potential risks that are associated with back pain. For those who develop back pain, targeted guideline advice [31] and reassurance [32] could be delivered via direct messaging services, accompanied with URL links to online interventions with dedicated webpages [33,34] and social media groups [35,36]. Refined data-filtering algorithms [13,37] and geo-location analyses [13,38] would further advance this area of research; and prospective-retrospective will help us understand the causal sequence and appropriate timing to guide online interventions.

Considering the massive burden of back pain, the current study provides a way forward for detecting at risk individuals through social media, which lays the platform from which we might inform targeted interventions delivered via social media.

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FIGURE LEGENDS

Figure 1. Case-crossover design. Red oval depicts the “hazard period”, defined as a 48 hour period immediately before the case tweet. Green ovals depict “control periods” defined as 2 weeks and 2 months before to the case tweet.

Figure 2. Frequencies of discordant pairs for Control 1 (2 week) and Control 2 (2 month) comparisons. Blue bars represent hazard discordant pairs (risk factor tweeted during the hazard, but not during control period). Red bars represent control discordant pairs (risk factor tweeted during the control, but not during hazard period).