A Method for Retrieval of Tweets About Hospital Patient Experience

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Abstract. Analysis of Twitter communications can capture data on hospital patient experience, and this will be more appropriate for hospital management and patient care because the data represent patients' and carers' experience about something as they happen. This paper reports on the development and testing of a semi-automatic method for retrieval of subsets of Twitter communications representing hospital patient experience on different topics and subtopics. Twelve main topics of discussions on patient experience have been identified. Furthermore, it has been demonstrated that it is possible to retrieve tweets on most of the topics by using pre-defined search strings comprising various terms that represent a given topic.

Terms: Twitter Analysis, Social Media, Patient Experience, Information Retrieval

1 Introduction

1.1 Hospital Patient Care

Management of patient experience and expectations is a core activity in any hospital. Capturing data and understanding individual patient experience is critical to overall patient care [1]. Previous research has highlighted the value of taking into account patients' own evaluation of their care [2]. A number of methods are used to collect data on patient experience in UK hospitals, for example,

- Through online tools like independent Care Opinion website (https://www.careopinion.org.uk/), or NHS Patient Opinion website (https://www.nhs.uk/aboutNHSChoices/aboutnhschoices/partners/patient-opinion/Pages/patient-opinion.aspx) that allow patients to submit their stories regarding their experience of care as a patient or service user or carer. The story they submit may be about a number of services across both health and social care. Once the story has been submitted it is moderated and published on the website. After publication the relevant staff in the care providers, commissioner or health board, regulator, patient organizations, and other local or national bodies are alerted. Staff are able to respond to the story without knowing who the author is and the author of the story can then respond to this. Changes are then made within the health service as appropriate.

- Through the NHS Choices website: The Patient and visitor information page of the Newcastle-hospitals website suggests patients and visitors submit feedback within hospitals via 'Take 2 Minutes... Tell us what you think' boxes in public areas or alternatively, if a patient has further concerns to contact the Patient Advice Liaison Service (PALS) or if they wish to make a complaint to contact the North East NHS Independent Complaints Advocacy.
- Friends and family Test: A further mechanism for gathering feedback from patients is the Friends and Family Test, where patients are all asked the following standard question "How likely are you to recommend our ward (or service) to your friends and family if they needed similar care or treatment?" Patients can respond to this question within hospitals, online, by text or by post.
- NHS Patient Surveys: There are also a number of surveys carried out by the Care Quality Commission (CQC) [3] including surveys relating to inpatients, outpatients, emergency departments, community mental health, and maternity.

The main criticisms of current methods of feedback are the purposeful nature of the feedback and the likelihood that those people with a particular issue to raise are most likely to provide feedback of either a positive or negative nature. Interviews have received criticism for encouraging negative responses whereas surveys have been criticised for bland positive response [4].

Research shows that analysis of communications on microblogging tools like Twitter reflects 'events and trends in users' real lives because many users post tweets related to their experiences.' [5] Consequently some researchers have demonstrated how Twitter communications can be analysed to generate useful information for decision making and improving services.

1.2 Patient Experience

Patient Experience covers many different aspects of a patient's journey through the healthcare system. Research undertaken by the National Health Service [6] has identified that patients care about their experience as much as their clinical effectiveness and safety. Patient experience has been identified by the government as a high priority and many initiatives are in place to work with patients to identify their needs.

Furthermore the importance of patient experience can be understood by its significance in key hospital policy frameworks. The NHS outcomes framework is a set of indicators developed by the Department of Health to monitor the health outcomes of adults and children in England. The framework provides an overview of how the NHS is performing. Within the framework there are five domains which focus on improving health and reducing health inequalities, The fourth domain focusses on patient experience: "Ensuring that people have a positive experience of care" [7]. Further to this, quality standards regarding patient experience have been established by NICE [8] to provide the NHS with clear guidance on the components of a good patient experience. The NICE guidelines developed in 2012 referred to 14 quality standards relating to patient experience which underpin the management of patient care. The quality standards provide guidance to ensure the patient experience is given due consideration in all aspects of hospital care.

Patient satisfaction measures are also increasingly used for benchmarking and accreditation purposes. Measures of patient satisfaction are considered indicative measures of service quality and quality of care. However, there is also evidence to suggest that currently the measurement of patient satisfaction and service quality is not an accurate reflection of what and how patients experience health care [9]. Furthermore, Doyle et al [10] reviewed the evidence from 55 studies to establish the links between patient experience and clinical safety and effectiveness and concluded that patients have a role to play as partners in identifying poor and unsafe practice and help enhance effectiveness and safety.

1.3 Related Works

Twitter is a free microblogging site in which users write brief snippets of information regularly, portraying emotions, opinions, interests etc. It has developed as a platform for consumers to express their feelings and opinions on almost all aspects of customer service and has become a very popular method of communication. As of the second quarter of 2017, Twitter averaged at 328 million monthly active users, who contribute an average of 500 million tweets each day [11]. The instant portal of communication allows this huge amount of users to provide feedback and seek solutions in a public platform [12]. Communications between consumers over Twitter was described by Jansen et al [13] as a type of electronic word-of-mouth. Due to the wide range of users from different social backgrounds, Twitter is also a good source of collecting consumer opinion, from ordinary people to professionals, organization representatives, celebrities and politicians. Thus, the tweets collected are the words of users with different interest groups and this makes it a very valuable online source of opinion.

Numerous research has taken place over the past years that aimed at developing methods and tools for extracting information from Twitter communications in different fields, including several in medicine and healthcare (see [14-26]). Many of these research have focused on developing novel tools using advanced linguistic and sentiment analysis techniques (see for example, [15, 27-32]), while others have used qualitative hybrid (a combination of quantitative and qualitative techniques for analysis of Twitter data) (see for example, [33-34]). Again, some researchers have aimed at developing tools for capturing some specific information from Twitter such as user locations (see for example, [31,32]).

Corley et al [27] examined mentions of influenza on social media by text mining, and noted that it was possible to detect trends in flu. Eichstaedt et al [35] examined the language used by individuals in social media and determined that the language used on Twitter could predict deaths from heart disease significantly better than a model combining 10 common demographic, socioeconomic, and health risk factors, including smoking, diabetes, hypertension, and obesity. Greaves and his associates [18,19] qualitatively analysed 1000 tweets, that were sent directly to hospitals, and concluded that only a small proportion of tweets directed at hospitals discuss quality of care. Following the work of Greaves this study aims to determine a method which improves the relevance of the tweets extracted and doesn't rely on the mention of a hospital name. In contrast to previous work, which identified tweets aimed at specific hospitals [18,19], the purpose of this study was to initially identify aspects of patient experience irrespective of the particular hospital or hospital trust.

2 Research Aims and Methods

2.1 Aims

The overall objective of this research is to develop a simple tool that can retrieve tweets that discuss hospital patient experience on specific topics which could be of value to hospital management to take measures for improvement of patient experience. In order to achieve this objective, this research aimed to investigate:

1. How can we identify the different issues or topics that are discussed by hospital patients and carers in relation to patient experience?
2. How can we prepare a list of topics and subtopics that describe patient experience in hospitals?
3. How can we create pre-defined search strings that can retrieve sets of tweets discussing hospital patient experience on a particular topic?
4. How effective and efficient would such predefined strings be in retrieving the relevant tweets?

2.2 Methods

A number of different methods are used for analysis of tweets, e.g. (a) sentiment analysis techniques where sentiment associated with words are identified and used to categorise or analyse tweets; (b) machine learning techniques that automatically categorise tweets into some pre-defined headings or classes; (c) social network analysis that analyses characteristics of user communities participating in Twitter communications on specific topics; and (d) qualitative analysis techniques like thematic and content analysis which are based largely on manual or semi-automatic analysis [36]. In the absence of any pre-defined categories or themes to represent hospital patient experience expressed thorough Twitter communications, this research resorted to using a combination of quantitative (term-based search) and qualitative analysis (manual investigation) techniques to identify the key themes or topics of discussion, and thus address the first two research questions which subsequently led to address the other questions.

In the first phase, a dataset of 7321 tweets was collected, using Twitonomy, using the terms hospital and #hospital. Each tweet was examined manually to remove all retweets, news items, and duplicate tweets, non-English and marketing related tweets. This left a sample of 4360 tweets. A manual analysis of the language used in the tweets of the resulting sample was undertaken. A grounded theory approach was used to identify the "tokens" or "terms" most commonly used. After a period of testing and a number of iterations it was concluded that the tweets which included **"I"** and **"this hospital"** identified tweets which most accurately conveyed personal hospital patient experience. This supports previous research [13, 37] which has identified tweets using personal pronouns and tweets expressing personal opinion as "Personal" Tweets.

In the second phase the terms "I" and "this hospital" were used on Twitonomy in order to collect a sample of tweets each month over a period of 6 months. This produced a second dataset of 5700 tweets, the majority being personal tweets. A thematic analysis [38] was undertaken to identify the emerging topics of discussions. As there were no preconceived ideas regarding the topics which were likely to emerge from the data, a grounded theory approach [38] was deemed most appropriate. It was expected that the themes or topics would emerge as the analysis took place. A grounded theory approach was employed to classify each tweet manually. The content of each tweet in the dataset was read and examined to identify a topic. The topic headings were initially assigned considering the main purpose of the tweet recognising that many tweets could logically fall within more than one topic. For example "I hate this" would be classified as Emotion, "I hate this hospital bed" would be classified as "Hospital facilities". The set of topics was expanded until no new topics emerged. When the process was completed for the dataset, 37 significant topics relating to patient experience were identified. Further manual examination of the data identified that some the original topics were too broad and there was some significant overlap. Subsequently, after a number of iterations and testing, the topics were consolidated to 12 because some topic had to be combined because of major overlaps. A number of tweets within the original dataset were identified as not fitting into the identified topics as they were either considered to be irrelevant or to be a general observation. Irrelevant Tweets were those which were not connected to a patient in hospital, and often associated with references to high profile medical cases which are featured in the media or hospital based films or television programmes, e.g."It totally disgusts me how this hospital treated tom Kate and Alfie, an animal would have been given better treatment". General observations included tweets which were connected to a stay in hospital but gave no insight into hospital patient experience, e.g.: "Soon as I get out this hospital, I gotta job waiting for me" or "I swear im always at this hospital". Although the refining of the topics reduced some duplication it is acknowledged that some tweets can still be classified into multiple topics. A reference set was created for future guidance on the selection and categorization of terms under each topic.

In the third phase a set of pre-defined search strings were created, with terms to represent each of the 12 main topics, that could be used to search for tweets on a specific topic. A set of tweets was collected using the terms "I" and "This hospital" for over one month, and 12 test collections were created taking the first 100 tweets from each results set where the set had more than 100 tweets. If a set had less than 100 tweets, it was ignored and the result for the following day was considered. Thus a collection 12 sets, with 100 tweet each, was built for the experiment. Each set was manually analysed and the number of tweets on each of the 12 main topics was noted. These figures were used to measure the recall of each search conducted in the following phase.

In the fourth phase, each test collection was searched with pre-defined search strings on each of the 12 topics, and the corresponding search results were noted and used to measure the recall and precision of the searches.

3 Results

3.1 Main topics

Table 1 shows the 12 main topics (and the corresponding terms/subtopics).

Table 1. Main topics and the corresponding terms/subtopics

Topic	Terms*	No. of terms
Wanting to leave	leave, get out, hours, go home, since, out of this hospital, out this hospital, all day, days, all night, stuck, waiting, leaving	13
Emotion	hate, bored, love, tired, sick, hope, cry, crying, laughing, scared, anxiety, miserable, upset, don't like, disgusted, frustrated, fun, happy, hopefully, lonely	20
Friends/family	baby, mom, family, dad, brother, sister, grandma, mum, mother, husband, cousin, mama, grandpa, granny, daughter, niece, friend, grandmother, mothers, pops	20
Hospital facilities	bed, cold, lost, bill, smell, smells, freezing, hot, cafeteria, parking, huge, room, uncomfortable, bathroom	14
Food	food, hungry, starving, coffee, eating, eat, lunch, breakfast, eaten, chocolate, starbucks, subway, pizza, starve, cafeteria, drink	16
Sleep	nurse, doctor, staff	3
Staff	sleep, sleepy, tired, nap, slept	5
Tweets by hospital staff	job, working, work, volunteer, interview	5
Telecommunication	wifi, phone, signal, text, tweets, charger, snap-chat, texting, tweeted, "poor connection", "win-dows vista", computer, data, emojis	14
Specific illness	sick, cancer, pain, disease, coughing, sicker, suicide, knee, shoulder, "back hurts", "body parts", "feel worse", "fighting for my life", "get better", "my back", A&E, aching, AH1N1, AIDS, allergic, arm, autism, blood pressure,	36

	breathing, chest, contractions, cough, diagnosed, eyes, fever, headache, kidney stones, labor, leg, liver, post-appendectomy	
Treatment	medicine, needle, meds, surgery, treatment, "IV line", chemo, appointment, drug	9
Entertainment	watch, tv, Netflix, watching, mtv, Disney, ESP, film, movies, playing, ps4,speakers	12

* a cut-off point of 90 was chosen, i.e. additional terms were found and added until a total 90% of the tweets on the given topic were retrieved using all the terms together.

As Table 1 shows Twitter users use words in a variety of forms. Some occur in multiple spellings or forms e.g. mom, mama, mother, etc. Other words have the same stem, e.g sleep, sleepy. Such variant forms of terms have not been combined just to show that variant forms of words are used in tweets; however, some terms, e.g. with the same stem, can be truncated when creating a string search. The total number of terms representing a topic (i.e. required to retrieve 90% of the tweets on the topic) varied from 3 to 37, with an average of 14. Within the "Staff" subset 90% of the original tweets which referred to staff were returned from just 3 terms: nurse, doctor and staff; however within the "Specific Illness" subset, 90% of tweets were returned from 37 terms, and yet this list may grow even bigger because some of the terms occurs only a few times.

3.2 Categorizing tweets in the test collections

Each of the 12 test datasets, comprising 100 tweets each, was manually analysed to identify the number of tweets on each topic. Although, as expected, some tweets were classed under more than one topic, no new topic was found. This demonstrates that although the first test collection comprising 5700 tweets, mentioned earlier, and the 12 test collections of 100 tweets each were collected at different times, all the communications on hospital patient experience can be categorized under one or more of the 12 broad topics as mentioned in Table 1.

3.3 Pre-defined Search Strings

All the terms under each topic listed in Table 1 were combined to create a pre-defined search string for the topic. Each dataset was then searched for each topic using the pre-defined search strings and the number of hits and the number of items retrieved for each search was noted. These figures were used to calculate the recall and precision.

3.4 Retrieval Effectiveness

Tables 2 and 3 show the recall and precision figures for each search on each of the 12 test collections.

Table 2: Measurement of Recall within each dataset

Dataset	Want to Leave	Emotion	Friends /family	Hospital Facilities - other	Food	Sleep	Staff	Staff Tweet	Tele-communication	Specific Illness	Treatment	Enter-tainment
1	62%	64%	86%	57%	86%	100%	67%	80%	33%	83%	63%	50%
2	81%	54%	57%	71%	86%	60%	60%	64%	100%	0%	75%	75%
3	76%	54%	60%	54%	83%	60%	60%	80%	0%	67%	80%	0%
4	73%	61%	100%	50%	78%	50%	86%	43%	100%	0%	100%	67%
5	77%	71%	85%	50%	83%	83%	71%	67%	50%	0%	50%	67%
6	81%	59%	83%	100%	83%	75%	100%	50%	0%	50%	57%	60%
7	83%	65%	88%	50%	100%	100%	92%	100%	75%	0%	50%	67%
8	86%	74%	100%	78%	91%	100%	100%	80%	100%	0%	86%	100%
9	86%	60%	100%	59%	80%	60%	78%	63%	0%	100%	75%	75%
10	95%	80%	86%	60%	80%	75%	100%	100%	50%	50%	67%	100%
11	88%	86%	100%	71%	86%	100%	89%	78%	100%	100%	67%	50%
12	80%	72%	75%	68%	100%	100%	100%	0%	100%	0%	50%	0%
Average	**81%**	**67%**	**85%**	**64%**	**86%**	**80%**	**84%**	**67%**	**59%**	**38%**	**68%**	**59%**

Table 3: Measurement of Precision of Tweets retrieved

Dataset	Want to Leave	Emotion	Friends/ family	Hospital Facilities - other	Food	Sleep	Staff	Staff Tweet	Tele-communication	Specific Illness	Treatment	Enter-tainment
1	59%	84%	86%	62%	60%	60%	50%	57%	100%	71%	100%	100%
2	61%	93%	62%	48%	67%	75%	50%	70%	100%	0%	75%	43%
3	89%	67%	50%	41%	56%	60%	75%	57%	0%	40%	80%	0%
4	76%	88%	63%	38%	100%	83%	55%	30%	100%	0%	100%	67%
5	77%	88%	73%	25%	63%	63%	63%	57%	100%	0%	67%	50%
6	73%	93%	91%	29%	83%	100%	33%	40%	0%	20%	80%	50%
7	81%	68%	88%	38%	75%	75%	100%	25%	60%	0%	75%	67%
8	76%	92%	50%	41%	71%	75%	100%	33%	100%	0%	67%	40%
9	83%	79%	73%	53%	67%	100%	100%	45%	0%	13%	75%	60%
10	68%	93%	86%	53%	80%	75%	100%	67%	50%	11%	80%	67%
11	71%	89%	90%	71%	86%	80%	80%	64%	100%	20%	50%	50%
12	65%	75%	75%	68%	75%	25%	90%	0%	67%	0%	80%	0%
Average	**73%**	**84%**	**74%**	**47%**	**73%**	**73%**	**75%**	**45%**	**65%**	**29%**	**77%**	**51%**

Note: Where measurement is shown as 0% there were no tweets relating to that topic within that particular dataset.

4 Discussions

Tables 2 and 3 and figure 1 show that the average recall was high (nearly 70%) with 80% or more for some topics. The precision figures for most of the topics were quite high with 70% or more for 7 topics. This demonstrate that it's possible to retrieve sets of useful tweets using pre-defined search strings for most of the commonly discussed topics about hospital experience. The average measurement of recall was found to be highest across all the topics within the Food topic at 86%. The level of precision was also found to be high at 73%. Perhaps unsurprisingly over 20% of the tweets were identified as emotion. The recall was found to be reasonably high within this topic and the precision was high. However, a high proportion of tweets within this topic were also attributed to other topics as patients expressed emotion relating to other factors. Tweets relating to 'friends and family' accounted for 10% of the dataset and again the recall and precision were high 85% and 74% respectively. The recall and precision of tweets associated with hospital facilities was surprisingly low at 64% and 47%. However, on further investigation this was mainly due to the use of the word bed. Although this had previously been found to be the term most frequently used when discussing hospital facilities and it was not identified as a term within another topic it was found to be used frequently within tweets relating to other topics e.g.

“Stuck in this hospital bed with this unseasoned diet 😂 i can't wait to recover so i can eat what i please”

The removal of the term “bed” from the search string may significantly increase the level of precision.

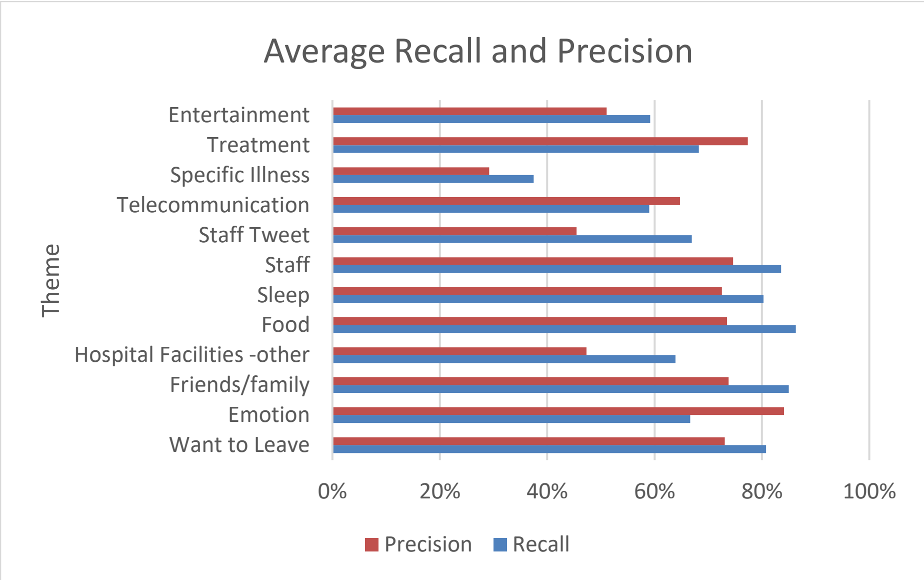

Figure 1: Recall-Precision figures for each topic

Both recall and precision were low (38% and 28% respectively) for the ‘Specific illness’ topic. This topic also had the maximum number of terms (37). This is particularly interesting when compared to the ‘Staff’ topic which has the lowest number of terms, and yet generated a high level of recall and precision. This suggests that the number of terms used to describe a specific illness is too high to automate and it may be more appropriate to merge with another topic such as Treatment.

The word “sick” can also fall into more than one topic. Within this study it has been classified as a term under both ‘Emotion’ and ‘Specific Illness’ which produces misleading results within the Specific Illness topic but has proved to be more accurate as a term associated with Emotion.

The level of recall and precision may also be limited in some of the topics because the number of tweets within the total dataset are very small. The subsets of tweets within the telecommunication, specific illness and entertainment topics are each less than 3% of the overall total dataset.

5 Conclusion

This study has established that the different topics discussed by hospital patients in relation to their experience can be identified by developing a method for the extraction of relevant tweets which uses search strings created from the most frequently used terms. It is noted that patients' communications can be broadly categorized into 12 topics, and they don't seem to change over a range of tweets collected at several intervals.

The range of level of recall and precision figures demonstrate the accuracy and relevance of a number of search strings created to capture discussions on specific topics. Thus the methodology has proved to be reliable for extracting tweets using the predefined search string for most of the topics that are discussed on Twitter describing patient experience. It is noted that for some topics the term sets need to be refined to remove those words which are either ambiguous or which are misleading, and hence they produce a lot of noise, and thus reduce precision.

Some topics, for example specific illness can be described by a large number of terms. Hence, it is difficult to come up with a search string that can be exhaustive enough to generate better retrieval of tweets. Further work is needed to identify more terms, if any, and to organize the terms into subcategories, e.g. in case of specific illness the type of illness may be classed under organ or disease class, which may be used to retrieve tweets on specific type of illness. It is acknowledged that further research may be needed to validate the topics and the corresponding search terms (a) using multiple sets of tweets collected at different times of the year, perhaps to see whether there are seasonal variations in terms of topics being discussed, and also (b) using other people as indexers to avoid any indexer biasness in categorizing topics under specific topics.

References

1. NHS Confederation homepage, http://www.nhsconfed.org, last accessed 2017/09/15
2. Yamamoto, S., Wakabayashi, K., Satoh, T., Nozaki, Y., Kando, N., (2017)..: Twitter user growth analysis based on diversities in posting activities. International Journal of Web Information Systems 13(4), 370–386
3. Cqc.org.uk. (2017). Care Quality Commission. [online] Available at: http://www.cqc.org.uk/ [Accessed 15 Sept. 2017].
4. Ahmed, F., Burt, J. and Roland, M., (2014). Measuring Patient Experience: Concepts and Methods. *The Patient - Patient-Centered Outcomes Research*, 7(3), pp.235-241
5. Al-Abri, R. and Al-Balushi, A., (2014) Patient satisfaction survey as a tool towards quality improvement. Oman Medical Journal, 29(1), 3-7
6. Nhs.uk. (2017). Patient opinion - NHS Choices. [online] Available at: http://www.nhs.uk/aboutNHSChoices/aboutnhschoices/partners/patient-opinion/Pages/patient-opinion.aspx. Last accessed 2017/09/27
7. NHS outcomes framework, 2017 https://www.gov.uk/government/publications/nhs-outcomes-framework-2016-to-2017Abirami, A. and Askarunisa, A. (2017). Sentiment analysis model to emphasize the impact of online reviews in healthcare industry. *Online Information Review*, 41(4), pp.471-486

8. NICE: National Institute for health and care excellence: Applying CG138 NICE patient experience in adult NHS services and QS15 NICE quality standard for patient experience in adult NHS services to complaints & the complaint process. (2014). https://www.nice.org.uk/sharedlearning/applying-cg138-nice-patient-experience-in-adult-nhs-services-and-qs15-nice-quality-standard-for-patient-experience-in-adult-nhs-services-to-complaints-the-complaint-process. Last accessed 2018/06/12
9. Schembri, S. (2015) Experiencing health care service quality: through patient' eyes. Australian health review, 39(1), 109-116
10. Doyle, C., Lennox, L. and Bell, D.: A Systematic Review of Evidence on the Links between Patient Experience and Clinical Safety and effectiveness, BMJ Open. 3(1). http://bmjopen.bmj.com/content/3/1/e001570. Last accessed 2018/06/12
11. Statista (2017) Number of active users 2010-2017 Available at: https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/ Last accessed 2017/09/30.
12. Morris, M.R., Teevan, J. & Panovich, K. (2010) What do people ask their social networks, and why?: a survey study of status message q&a behavior. In Proceedings of the SIGCHI conference on Human factors in computing systems (pp. 1739-1748). ACM
13. Jansen, B. J., Zhang, M. M., Sobel, K. & Chowdury, A. (2009) Twitter Power: Tweets as Electronic Word of Mouth. Journal of the American Society for Information Science and Technology, 60, 2169-2188.
14. Ahmed, W., Bath, P., Sbaffi, L., Demartini, G. (2018) Measuring the Effect of Public Health Campaigns on Twitter: the Case of World Autism Awareness D. In: Chowdhury, G., McLeod, J., Gillet, V. and Willett, P. (eds). iConference2018, Sheffield, march 25-28, 2018, Springer, LNCS 10766, Springer, Heidelberg
15. Akay, A., Dragomir, A. & Erlandsson, B. E (2015) Network-Based Modelling and Intelligent Data Mining of Social Media for Improving Care. IEEE Journal of Biomedical and Health Informatics, 19, 210-218
16. Farrington, C., Burt, J., Boiko, O., Campbell, J. and Roland, M. (2017) Doctors' engagements with patient experience surveys in primary and secondary care: a qualitative study. Health Expect, 20: 385–394. doi:10.1111/hex.12465
17. Galloro, V. (2011) Status update. Hospitals are finding ways to use the social media revolution to raise money, engage patients and connect with their communities. Modern healthcare, 41, 6-7, 16, 1.
18. Greaves, F., Ramirez-Cano, D., Millett, C., Darzi, A. & Donaldson, L. (2013) Harnessing the cloud of patient experience: using social media to detect poor quality healthcare. Bmj Quality & Safety, 22, 251-255.
19. Greaves, F., Laverty, A. A., Cano, D. R., Moilanen, K., Pulman, S., Darzi, A. & Millett, C.(2014) Tweets about hospital quality: a mixed methods study. Bmj Quality & Safety, 23, 838-846
20. Hemsley, B., Palmer, S. & Balandin, S. (2014) Tweet reach: A research protocol for using Twitter to increase information exchange in people with communication disabilities. Developmental Neurorehabilitation, 17, 84-89
21. Kuang, S. and Davison, B. (2017) Learning Word Embeddings with Chi-Square Weights for Healthcare Tweet Classification. Applied Sciences, 7(8), p.846.
22. Lee, J. L., Decamp, M., Dredze, M., Chisolm, M. S. & Berger, Z. D. (2014) What Are Health-Related Users Tweeting? A Qualitative Content Analysis of Health-Related Users and Their Messages on Twitter. Journal of Medical Internet Research, 16, 122-130.

23. Misopoulos, F., Mitic, M., Kapoulas, A. & Karapiperis, C. (2014) Uncovering customer service experiences with Twitter: the case of airline industry. Management Decision, 52, 705-723.
24. Scanfeld, D., Scanfeld, V. and Larson, E. (2010) Dissemination of health information through social networks: Twitter and antibiotics. American Journal of Infection Control, 38(3), pp.182-188.
25. Atefeh, F. & Khreich, W., (2015) A survey of techniques for event detection in twitter. Computational Intelligence, 31(1), pp.132-164
26. Giachanou, A., Harvey, M. and Crestani, F. (2016) Topic-specific stylistic variations for opinion retrieval on twitter. In European Conference on Information Retrieval (pp. 466-478). Springer International Publishing.
27. Corley, C. D., Cook, D. J., Mikler, A. R. & Singh, K. P.(2010) Text and Structural Data Mining of Influenza Mentions in Web and Social Media. International Journal of Environmental Research and Public Health, 7, 596-615.
28. Giachanou, A., Harvey, M. and Crestani, F. (2016) Topic-specific stylistic variations for opinion retrieval on twitter. In European Conference on Information Retrieval (pp. 466-478). Springer International Publishing
29. Huang, F. L., Zhang, S. C., Zhang, J. L. & Yu, G. (2017) Multimodal learning for topic sentiment analysis in microblogging. Neurocomputing, 253, 144-153.
30. Jain, V. K., Kumar, S. & Fernandes, S. L. (2017) Extraction of emotions from multilingual text using intelligent text processing and computational linguistics. Journal of Computational Science, 21, 316-326.
31. Inkpen, D., Liu, J., Farzindar, A., Kazemi, F. and Ghazi, D. (2017) Location detection and disambiguation from twitter messages. Journal of Intelligent Information Systems, 49(2), pp.237-253.
32. Jain, A. and Jain, M. (2017) Location based Twitter Opinion Mining using Common-Sense Information. Global Journal of Enterprise Information System, 9(2), p.28.
33. Lee, J. L., Decamp, M., Dredze, M., Chisolm, M. S. & Berger, Z. D. (2014) What Are Health-Related Users Tweeting? A Qualitative Content Analysis of Health-Related Users and Their Messages on Twitter. Journal of Medical Internet Research, 16, 122-130
34. Dodd, L., Chowdhury, G. and Walton, G. (2017) Information Seeking Behaviour of Aspiring Undergraduates on Social Media:Who are They Interacting with? In: Choemprayong**,** Songphan, Crestani**,** Fabio, Cunningham**,** Sally Jo (Eds.) ICADL2017, Bangkok, 13-15 November, 2017. Springer, LNCS10647, 245-255. Springer, Heidelberg
35. Eichstaedt et al .(2015) Psychological Language on Twitter Predicts County-level Hearth Disease mortality. Psychological Science. 26(2), 159-169,
36. Batrinca, B. and Treleaven, P. (2014) Social media analytics: a survey of techniques, tools and platforms. AI & Society. 30(1), 89-116,
37. Honeycutt, C. and Herring, S. (2009) beyond Microblogging: Conversation and Collaboration via Twitter. In: Proceedings of the 42nd Hawai International Conference on System Sciences (HICSS-42), Los Alamitos, CA: IEEE Press. http://ella.slis.indiana.edu/~herring/honeycutt.herring.2009.pdf. Last accessed 2018/06/12
38. Clarke, V. and Braun, V. (2016) Thematic analysis. The Journal of Positive Psychology, 12(3), pp.297-298.
39. Glaser, B.G. and Strauss, A.L. (1967) The Discovery of Grounded Theory. Aldine.