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Using natural language processing to understand, facilitate and maintain continuity in patient experience across transitions of care

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ABSTRACT

Background: Patient centred care necessitates that healthcare experiences and perceived outcomes be considered across all transitions of care. Information encoded within free-text patient experience comments relating to transitions of care are not captured in a systematic way due to the manual resource required. We demonstrate the use of natural language processing (NLP) to extract meaningful information from the Friends and Family Test (FFT).

Methods: Free-text fields identifying favourable service ("What did we do well?") and areas requiring improvement ("What could we do better?") were extracted from 69,285 FFT reports across four care settings at a secondary care National Health Service (NHS) hospital. Sentiment and patient experience themes were coded by three independent coders to produce a training dataset. The textual data was standardised with a series of pre-processing techniques and the performance of six machine learning (ML) models was obtained. The best performing ML model was applied to predict the themes and sentiment from the remaining reports. Comments relating to transitions of care were extracted, categorised by sentiment, and care setting to identify the most frequent words/combinations presented as tri-grams and word clouds.

Results: The support vector machine (SVM) ML model produced the highest accuracy in predicting themes and sentiment. The most frequent single words relating to transition and continuity with a negative sentiment were "discharge" in inpatients and Accident and Emergency, "appointment" in outpatients, and "home' in maternity. Tri-grams identified from the negative sentiments such as 'seeing different doctor', 'information aftercare lacking', 'improve discharge process' and 'timing discharge letter' have highlighted some of the problems with care transitions. None of this information was available from the quantitative data.

Conclusions: NLP can be used to identify themes and sentiment from patient experience survey comments relating to transitions of care in all four healthcare settings. With the help of a quality improvement framework, findings from our analysis may be used to guide patient-centred interventions to improve transitional care processes.

1. Introduction

Understanding patients' experiences is important to guide the provision of safe, high-quality care and is therefore an increasing priority for healthcare organisations engaging in a culture that recognises patient-centric models of care delivery.[1] The Friends and Family Test (FFT) has been available in the National Health Service (NHS) in England for providing patient experience feedback.[2] Since implementation, the FFT has produced over 30 million pieces of feedback. In addition to quantitative, structured response questions, the FFT also allows patients to give feedback in their own words, via free-text comments, providing an additional data-rich source of information for quality improvement (QI). These free-text comments can be especially valuable if they are reported and analysed with the same scientific rigour already accorded to structured surveys [3,4]. However, this process is limited by human resource and the lack of a systematic way to

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extract the useful insights from patient free-text comments to facilitate QI.

Patients are keen to share both positive and negative experiences of their care and enter a dialogue on their experience of delivered care processes and how they could be improved, as needed.[5–7] Transitions of care have emerged as an important point of vulnerability in the healthcare system.[8] Transitions of care can lead to poor patient experience, complications, and outcomes, with some studies finding up to one-fifth of patients experience an adverse event within two weeks of hospital discharge, many of which could be prevented or mitigated with timely intervention.[9] Transitions of care are often complex, dynamic and involve multiple stakeholders and settings; characteristics that may render patient feedback unsuitable to quantitative analysis.

Several studies have demonstrated the applicability of natural language processing (NLP) and machine learning (ML) on free-text patient feedback data. [10–15] NLP has been used to classify comments by topics (topic classification) and to encode the polarity of sentiment expressed within a comment (sentiment analysis). Topic classification and sentiment analysis are useful and practical tools to identify specific free-text comments that cover a wide range of patient experiences within a large dataset. Furthermore, themes separated by sentiment can be extracted from free-text comments, highlighting areas of concerns and providing the context and details required from staff to rapidly learn and act on patient feedback.[16]

Further studies have explored the use of NLP to extract of meaningful information from patient feedback generating essential insights into the experience of patients [12–14,17–20]. Majority of these studies have applied NLP to online patient reviews from social media sites. A handful [12,14,18–20] have used NLP to complement structured surveys incorporating free-text patient feedback. NLP-based tools, however, remain a nascent technology to healthcare. It is so far limited to research environment and serves more to supplement the analysis of structured data, as opposed to a primary tool. This study aims to determine whether NLP and ML can reliably extract themes and sentiment relating to transitions of care and continuity from the FFT free-text in order to provide meaningful information.

2. Methods

2.1. Setting

This study was conducted at a large London NHS Trust. The hospital caters for a population of approximately 1,000,000 people across five sites. Care settings include accident and emergency (A&E), inpatient, outpatient and maternity, which routinely collect FFT patient experience data.

2.2. Data collection

The combination of NLP and ML are explored using the FFT free-text comments from January to July 2017 across four healthcare settings in a single teaching Hospital. Free-text comments were examined in response to the questions: “What did we do well?” and “What could we do better?”. This study received ethical approval from North East – Tyne and Wear South Research Ethics Committee, 17/NE/0306.

2.3. Qualitative content analysis

Deductive qualitative content analysis approach was used to manually code free-text comments from FFT survey from all four care settings into themes according to the 2011 English National Health Service Patient Experience Framework.[21] Each question was ascribed a minimum of one theme. Transition and continuity is one of the themes included in the framework, defined as ‘information that will help patients care for themselves away from a clinical setting, and coordination, planning and support to ease transitions’. Ten percent of free-text responses from each care setting were coded according the framework with the help of the mapping exercise by three independent annotators (MK, SHW and DM); a Clinician, the Head of patient experience with a nursing background, and a lay representative. Each comment was iteratively revealed to the annotator. No context was given to the response; only the free text in focus was presented for annotation, along with the topic labelling choice. Each comment was labelled with one theme from the framework. This template informed the training dataset required for topic classification. Independent inter-rater coding was calculated. It ensured that the learning template had limited personal bias, thus increasing the credibility and dependability of the final template.

2.4. Machine learning approach

The ML approach involved two steps; (i) pre-processing the data and (ii) text classification. In pre-processing, free-text comments were ‘standardised’ to build a representation of the data. In text classification, an algorithm decides which category (theme) each comment falls into. The Konstanz Information Miner (KNIME), an open-source and free data analytics platform, was used to explore the ability of supervised learning to produce meaningful insights into patient experience data. KNIME is an extensible program utilising workflow-based structures and open-source plugins to enable easy access to data extraction, transformation and advanced analysis, including NLP and ML.

2.5. Pre-processing of data

This was done by removing numbers and words with two characters or less, converting all upper case to lower case and removing punctuations. Certain words that do not add any meaning to the text known as “stop words” were eliminated to simplify the dataset. Typographical error and misspellings were not corrected.

2.6. Text classification

A supervised learning approach was used to predict the category (theme) from the free-text comments. A number of different technical approaches can be taken to classification in ML. We applied six ML models to classify comments and assess their performance using the training set. The six models were based on a systematic review on the used on NLP and NL to process and analyse free-text patient experience data.[22] The models included decision tree, random forest, SVM, K nearest neighbour, naïve bayes and gradient boosted trees. Model performance was measured as overall accuracy, recall, precision, and by the f-score which describes overall performance. We performed 10-fold cross-validation to evaluate the algorithms by partitioning the manually coded data set into a training set to train the model, and a test set to evaluate it. The ML model with the highest accuracy was applied to the rest of the comments to predict the themes from the patient experience framework.

2.7. Sentiment analysis

An equivalent supervised approach was undertaken to perform sentiment analysis, which uses patterns among words to classify a comment into a complaint, or praise. For sentiment annotation, the same dataset labelled for test classification above was given to the same annotator. The annotator would select a label by entering either 1 (positive), −1 (negative), or 0 (neutral). Each question was ascribed a minimum of one sentiment. The ML model with the highest accuracy was applied to the predict the sentiment within the rest of the FFT comments.

2.8. Identifying comments relating to transition and continuity

The remit of this study was to focus on the comments only relating to transitions of care. Therefore, using the best performing ML model based on overall accuracy, we extracted all the comments under the theme ‘transition and continuity’. For this analysis, we used the “bag of words” approach, which is the total body of words analysed (known as corpora) represented as a simplified, unordered collection of words. Tri-grams (3-word phrase) were used as the basic unit of analysis, as they provided more context as opposed to n-grams (single elements or words) or bi-grams (2-word phrase). Tri-grams were displayed in descending order according to frequency of occurrence, and further cleaned to remove repetitions of previously occurring tri-grams. Tri-grams related to ‘transition and continuity’ were further refined based on sentiment and healthcare setting.

A word cloud was created to illustrate single words, and the importance of each word is shown with font size and colour, which is useful for quickly perceiving the most prominent terms and for locating a term to determine relative prominence in relation to ‘transition and continuity’. The larger the word in the visual the more common the word was in the document(s). Evidence [14,19] suggests that word combinations (bigrams, trigrams, or n-grams) in NLP may bring to light an aspect that is not obvious when looking at just most common words. Similarly, combining analysis of bigrams with common word frequencies as well as with care aspects reveals more nuance and insight than with assessment of simple frequencies alone. Fig. 1 displays the steps taken after utilising the best ML model to identify comments related to ‘transition and continuity’ (see Fig. 2).

3. Results

A total of 69,285 FFT free text responses were analysed. Average character count to the question: “What did we do well” and “What could we do better” was 52 and 79 respectively. Average percentage of missing responses to the question: “What did we do well” and “What could we do better” was 2.7% and 31.2% respectively. Table 1 illustrates the inter-rater agreement (Cohen’s Kappa) amongst the three annotators according the Patient Experience Framework themes and Sentiment, in all four care settings. There is substantial agreement with themes and almost perfect agreement with sentiment.

Manual classification of comments within each question revealed that the individual question did not determine the sentiment, i.e., responses to the question “What did we do well?” could have a positive, negative or equivocal sentiment, and this was similar for the question “What could we do better?”.

3.1. Performance metrics

The ML model that produced the highest accuracy was Support Vector Machine (SVM) to the question “What could we do better” in Inpatient, Outpatient, A&E and maternity, 72.2%, 74.5%, 71.5% and 62.7% respectively. The accuracy for the other models (SVM and NB [naïve bayes]) can be found on Table 2. On the same question, Cohen’s kappa revealed substantial agreement (0.64) in Inpatient and moderate agreement (0.51, 0.60, 0.50) in Outpatient, A&E and maternity, respectively. Similar results were demonstrated to the questions “What did we do well”. The F-measure from the SVM model was 0.94 for theme related to ‘transition and continuity’ in inpatients, with a similar trend in the other care settings.

3.2. Word cloud relating to ‘transition and continuity’

Word clouds were generated to demonstrate the visual representation of the text data, which is a visualisation of term or word frequency from the bag of words. Term frequency of all negative sentiments relating to the theme ‘transition and continuity’ were extracted to create word clouds. They are all presented as an inside out word cloud with image exported as scalable vector graphics. The two most prominent words in outpatient were “appointment” and “doctor”, in inpatient,

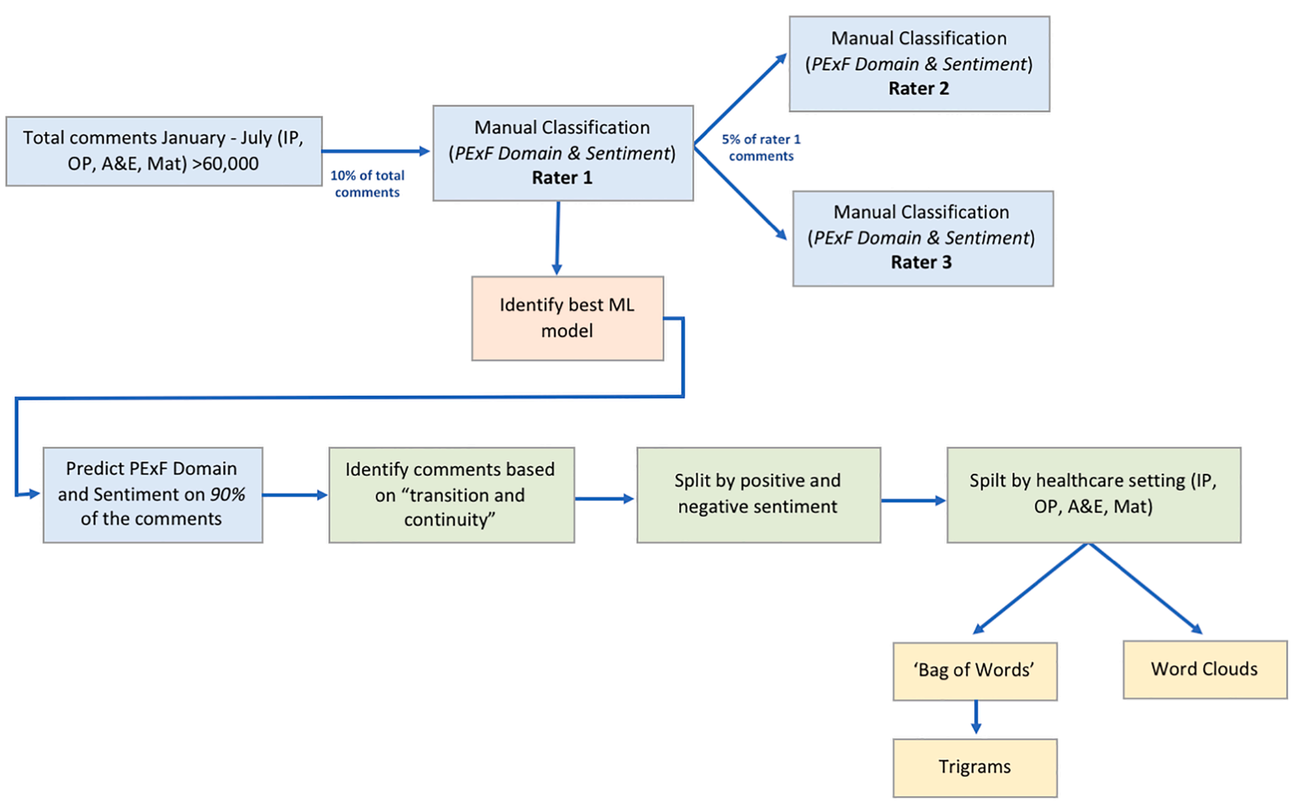

Fig. 1. Flowchart depicting the steps required to identify comments based on ‘transition and continuity’ which are then separated by sentiment, healthcare setting and finally displayed as tri-grams or word clouds. IP; Inpatient, OP; Outpatient, A&E; Accident and Emergency, Mat; Maternity, PExF; Patient Experience Framework (2011).

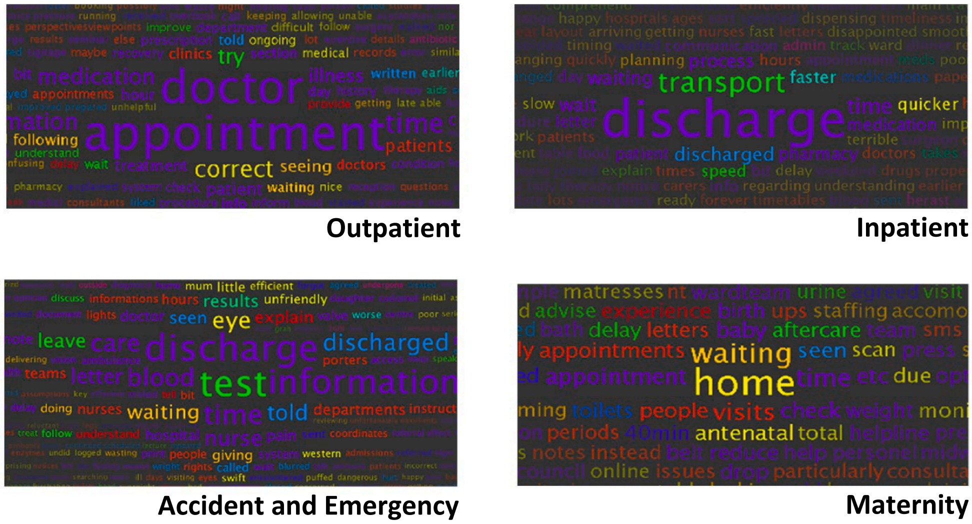

Fig. 2. Word cloud representations related to 'transition and continuity' based on negative sentiments in all four care settings. The larger the word, the more frequent it appeared in the comments.

Table 1A
Interrater agreement on the question *"What did we do well?"*

	Inpatient		Outpatient		A&E		Maternity	
	PExF Theme	Sentiment	PExF Theme	Sentiment	PExF Theme	Sentiment	PExF Theme	Sentiment
Rater 1 and 2	0.721	0.826	0.747	0.945	0.816	0.918	0.787	1.0
Rater 1 and 3	0.793	0.793	0.838	0.945	0.862	0.918	0.817	1.0
Rater 2 and 3	0.860	0.885	0.724	0.895	0.787	0.847	0.798	1.0

Table 1B
Interrater agreement on the question *"What could we do better?"*

	Inpatient		Outpatient		A&E		Maternity	
	PExF Theme	Sentiment	PExF Theme	Sentiment	PExF Theme	Sentiment	PExF Theme	Sentiment
Rater 1 and 2	0.646	0.952	0.852	0.825	0.847	0.838	0.941	0.833
Rater 1 and 3	0.655	1.0	0.873	0.748	0.903	0.840	0.9111	0.764
Rater 2 and 3	0.778	0.952	0.883	0.744	0.827	0.866	0.970	0.813

A&E, Accident and Emergency; PExF; Patient Experience Framework (2011).

Table 2
Percentage accuracy for the tow top performing models for each question on the FFT survey.

	What did we do well?	What could we do better?
SVM		
Inpatient	70.1	72.2
Outpatient	73.1	74.5
A&E	66.5	71.5
Maternity	63.1	62.7
NB		
Inpatient	57.9	59.3
Outpatient	61.5	66.7
A&E	53.6	55.1
Maternity	50.2	52.4

SVM Support Vector Machine; NB Naïve Bayes.

"discharge" and "transport", in A&E, "test" and "discharge" and in maternity, "home" and "waiting". Fig. 3 shows these word clouds displayed with all rows within the pre-processed document to enhance the key words for all four care settings.

Next we spilt all the comments in relation to the theme 'transition and continuity' according to the sentiment, i.e., positive and negative. The total number of tri-grams with an associated negative sentiment from outpatient, inpatient, A&E and maternity were 3109, 746, 2072 and 322 respectively. When split by positive sentiment there was a smaller total number of tri-grams (Fig. 3). However, in maternity the number of tri-grams with a positive sentiment was larger than with a negative sentiment.

We removed repeats and selected the highest 10 tri-grams based on descending order of frequency. Tri-grams with a frequency of greater than 10 were documented. Tri-grams related to 'transition and continuity' with an associated negative sentiment from each healthcare setting is presented in Table 3. The content of tri-grams varied depending on the healthcare setting, revealing a varied picture of what aspects of transition and continuity are important to patients as determined by their care episode.

4. Discussion

This study has demonstrated that NLP can be used to extract and analyse unstructured feedback by discovering words or combination of words appearing most frequently in comments such as transitions of care, which may not be accessible from quantitative analysis alone. Analysis of free-text responses has previously generated important insights into the experience of patients. [10–14,17]. However, to our knowledge this is the first study that demonstrates the use of NLP on

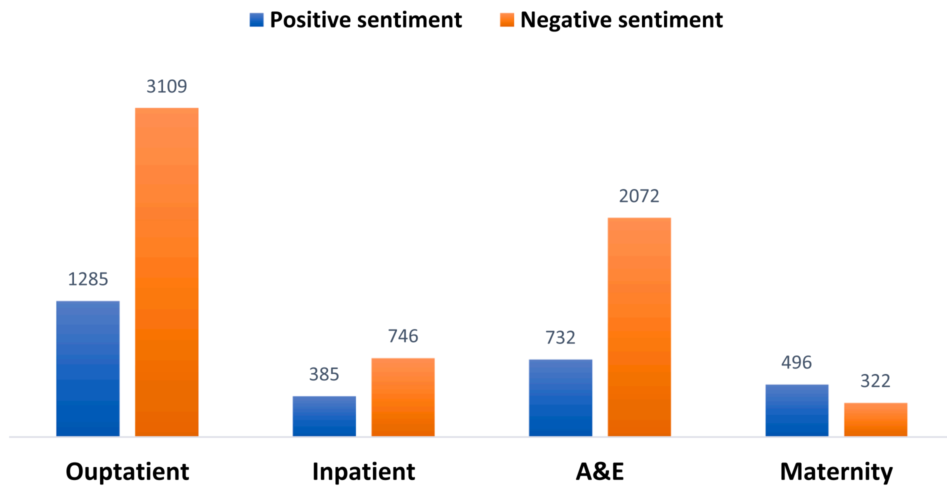

Fig. 3. The number of tri-grams relating to the theme 'transition and continuity' separated by negative and positive sentiment.

free-text FFT data.

Word combinations such as tri-grams bring to light an aspect that is not obvious when looking at just most common words. Similarly, combining sentiment analysis reveals more nuance and insight than with assessment of simple frequencies alone. For a limited amount of data, NLP may not be very expedient. Techniques such as trigrams rely on repetitive words and word combinations and with a smaller number of comments, the results may not be as fruitful and there may not be enough raw data to detect a specific pattern. On the other hand, NLP offers an advantage for large datasets such as FFT surveys and the free-text component as it provides the sophisticated tools to understand it. By identifying patterns, NLP processes can also direct stakeholders and identify comments that may carry more useful information and help to decrease manual analysis.[19] We uncovered marked differences within the comments relating to transition and continuity between the four care settings based on sentiment, demonstrated by the tri-grams and word cloud. This approach allows monitoring and improvement of targeted processes based on service or research priorities, whilst collecting feedback across all patient experience themes. Themes identified through analysis with NLP can be used to guide further, more targeted, qualitative research.

This near real-time approach facilitates feedback to be actioned appropriately and rapidly, thereby minimising the impact of ongoing service problems or errors being replicated. In this way there is a shift of resource, that was previously required for manual analysis and is now allocated to driving QI. It is important to note that this approach does not distort the original patient narrative. Even though pre-classified, understanding what the comments are specifically talking about still requires reading through the comments. This is in keeping with Guetterman T et al, [17] who compared traditional qualitative text analysis and NLP analysis. They found although NLP provides both a foundation to code qualitatively more quickly and a method to validate qualitative findings, it shouldn't replace in-depth manual analysis. NLP makes the process efficient by identifying trends in the comment.

We noted a higher average character count (79) in the responses and a higher average percentage (31.2%) of missing responses to the question, "What could we do better", compared to the question, "what did we do well". The number of tri-grams were higher in comments with negative sentiment compared to positive sentiment. This suggests that displeased patients do voice their concerns however less frequently, whereas majority of the patients are pleased about their experience and therefore provide little feedback. Wagland et al. [12] found that the content of positive comments was usually much less specific than that for negative comments.

5. Lessons for transitions of care and continuity

Patients' experiences of care transitions and continuity have previously been studied using several methods including interviews and surveys. Previous studies have identified that patients may find healthcare services difficult to navigate, disempowering, burdensome, and frustrating.[23] Patient feedback relating to transitions has previously revealed problems with care continuity [24] such as communication deficits and medication errors.[25–27] Consistent with the findings from this study, patients often identify a disjointed system in which organisational processes may be prioritised over individual needs.[27] Tri-grams identified in this study such as 'seeing different doctor' and 'information aftercare lacking' have not only highlighted problems with care transitions, but also identified potential improvements to care processes. Previous studies have also highlighted an emergence of 'transition and continuity' in the free-text comments using NLP. [12–15] We were able to demonstrate that the experiences of patients change as they encounter different care settings, and this was evident from the tri-grams and world cloud. The word "discharge" was highlighted due to the highest frequency in word clouds related to inpatient and A&E, indicating this is a particularly important transition of care process from the patient perspective. A similar finding was noted by Nawab et al [19], where there were more negative than positive comments around discharge.

For patients, transitioning through the continuum of care is a complex and dynamic process involving multiple stakeholders. Patients with complex care needs are particularly vulnerable to experiencing poor care quality as they move between multiple settings and come into contact with several providers.[28] Several of the tri-grams identified in this study, such as 'info discharge process', 'communicate friend discharge', 'inform patients delay', and word cloud words such as 'information' have highlighted the importance of communication during transitions of care.

5.1. Limitations

This study included FFT responses from a single hospital. A wider sample from additional hospitals might generate different views and improve generalisability of the findings relating to transitions of care and continuity. The amount of pre-processing required for the FFT free-text was carefully adjusted to avoid losing context and meaning from excessive pre-processing due to the short character count within the comments. There was a significant amount of similarity between the tri-grams in each column, which could be refined with further pre-processing with a larger average character count.

Table 3
Trigrams relating to transition and continuity and associated sentiment in four healthcare settings.

Outpatient		Inpatient	
Negative	**Positive**	**Negative**	**Positive**
appointment was given	Post operative care	Waiting time discharge	Ensure discharge safe
See same doctor	Time physio seen	Improve discharge process	Ensure home discharge
See same consultant	Consideration treatment options	Timing discharge letter	Discharge planning assess
Seeing different doctor	Advice follow consultation	Fast track discharge	Discharge carefully planned
Doctor next appointment	feel safe hands	Shorten waiting discharge	Communicate friend discharge
Give correct medication	concerns discussed thoroughly	Longer wait medications	Fell operation explanation
Doctor did know	Registrar read notes	Info discharge process	Procedure explained staff
Seeing different doctor	Consultant particular explained	Quicker discharge papers	Ward home quickly
get correct medication	Left feeling happy	Discharge letter doctor	Fast surgery recovery
Correct medication illness	Exercises explain well	Transport did come	Managed discharge efficiently
A&E		**Maternity**	
Negative	**Positive**	**Negative**	**Positive**
Forgot blood test	Immediate attention nurse	More home visits	Delivery post natal
Take blood test	Instructions follow thank	Home antenatal appointments	Reassured care staff
Discharge knowing information	Timely due care	Inform patients delay	Staff fantastic explained
Explain doctors nurse	Advice friendly staff	Sending sms home	Available short notice
Left waiting room	Diagnosis information deal	information aftercare lacking	Attention post section
Left long waiting	Follow treatment transfer	Preventable delays mistakes	Discharge staff fantastic
Nurses triage unfriendly	Referred relevant department	Inform patients delay	Section smoothly recovery
Was told sit	Explanation treatment triage	Patients leave home	Post operation care
Felt ill ambulance	Easy understand follow	Being born home	Tuition breast feeding
Small errors cause	Useful follow advice	Moved recovery labour	Post section dealt

6. Conclusion

Using NLP, we were able to identify multiple issues related to transitions of care and continuity within the FFT free-text data in an efficient way that did not require reading through all the feedback. Specific issues identified such as lack of information and poor discharge processes can be used to guide improvements in transition of care and continuity processes by utilising a quality improvement framework. We recommend that other healthcare services take advantage of these tools to actively generate insight from the free-text patient experience feedback and use it to guide care delivery in a timely manner.

7. Funding statement

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8. Summary points

What is already known?

- Transitions of care are often complex, dynamic and involve multiple stakeholders and settings; characteristics that may render patient feedback unsuitable to quantitative analysis.
- The ability to analyse and interpret free-text patient experience feedback falls short due to the resource intensity required to manually extract crucial information.
- A semi-automated process to rapidly identify and categorise comments from free-text responses may overcome some of the barriers encountered, and this has proven successful in other industries.

What does this study add?

- Supervised learning can identify themes, sentiment and trends in free-text patient experience feedback, which cannot be gleaned from quantitative data alone.
- Extracting comments relating to transitions and continuity labelled according to sentiment can provide meaningful information without the need for manually review.
- We revealed that patients' experience on transitions of care vary in each service setting, highlighting areas that require improvement.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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