Patients’ written reviews on NHS general practices: a valuable information resource

Contents

Introduction

Vast amounts of patient-generated reviews of GP practices which are collected by NHS can be used in more ways than what is the current practice. They can be processed to obtain insight into patient preferences with machine learning algorithms such as topic modelling (Chaney & Blei, 2012) in order to boost the pace of organisational learning in NHS. Online reviews are a resource which is already widely used in commercial applications to boost companies profitability and sales (Hogenboom, Frasincar, Kaymak, de Jong, & Caron, 2016). Commercial uses of the customer reviews data, however, are likely different from how public organisations such as NHS would like to make use of their patients’ reviews. This study explores the usefulness of patient reviews processed with topic modelling, a machine learning algorithm, for public organisation management. Written patient reviews of NHS funded GP practices in England are the example dataset in use. It is argued that anonymous online reviews could be used as a resource for boosting organisational learning in the public sector. The study includes suggestions for how to use the data in management of GP practices at a national level, and offers ideas for how to overcome unknown opinion biases which exist in data published online by large numbers of anonymous reviewers.

Literature review

National Health Service in United Kingdom does not seem to consider customer feedback in a similar fashion to how private retailers treat it (Tingle, 2014). Unfortunately, the NHS standards for complaint handling appear relatively low (ibid.). Patients file very large numbers of complaints because they are not informed well about the outcomes of their diagnosis and treatment, due to lack of necessary provisions such as pillows or blankets in hospitals, or due to shortcomings in how NHS workers take responsibility for their patients (ibid.). At present, online feedback on NHS GP services in England informs only individuals directly involved with commented-on NHS GP services such as patients and GP practice workers and managers (Trigg, 2016). For example, patients' feedback is known to correlate with how well NHS staff feel about their place of work (Raleigh, Hussey, Seccombe, & Qi, 2009) and can effectively be used to support implementation of improvements in management practices of individual public institutions (Di Pietro, Guglielmetti Mugion, & Renzi, 2013). Text reviews can also be used to inform about differences between health service providers that in conventional measures of performance score very similarly (Alemi, Torii, Clementz, & Aron, 2012; James, Calderon, & Cook, 2017). Beyond the level of individual organisations, the patients also have an interest in making sure the whole NHS works effectively (Mason, Baker, & Donaldson, 2011). As far as they understand healthcare, in reviews they write that they would like to see knowledgeable and caring medical professionals equipped with facilities which enable provision of high quality services (Lopez, Detz, Ratanawongsa, & Sarkar, 2012). It appears that the interests of the public expressed through written feedback are highly relevant to achieving a successful public health service and should not be overlooked.

In absence of good practices of customer review analysis done by public organisations (Hogenboom et al., 2016), a study involving customer feedback about NHS services can take inspiration from analytical work for private sector organisations (ibid.). Previous studies helped improve the quality of products and services (ibid.), detect specific desirable or undesirable behaviours online (Hogenboom et al., 2016; Law, Gruss, & Abrahams, 2017) and helped increase product sales and profitability (Deane, 2012; Glovinsky & Kim, 2015; Qi, Zhang, Jeon, & Zhou, 2016). The commercial examples of analysis of customer feedback appear especially helpful for public institutional settings when the objective of data analysis is to achieve similar goals to those of commercial companies, such as using customer feedback to make provision of services more financially lean (Di Pietro et al., 2013). On the other hand, oftentimes the needs of public organisations are different because they have "forced customers" as opposed to clients that have some choice (ibid.) and their objectives may be unrelated to service demand or profitability (Brownson, Allen, Duggan, Stamatakis, & Erwin, 2012). For example, a manager in a private GP surgery can reasonably assume that simply making patients happy stands for a high quality service (e.g. James et al., 2017). In the case of public healthcare, however, questions may be asked about whether the services which made the customer happy were all really necessary, and whether the treatment method ensured the most cost-effective care available equally to all. Therefore, the purpose and interpretations of analyses of customer feedback for public institutions may diverge from how private service providers would use them. The question how to analyse customer feedback for public organisations, especially in case of public healthcare, constitutes a gap in literature that needs to be addressed.

The choice of the best technique to extract information from written customer feedback depends to a large degree on how many reviews there are available (Hogenboom et al., 2016). Smallest review datasets, such as the one investigated by Lopez et al, contain numbers of reviews which can be read manually in a systematic manner (Lopez et al., 2012). With small datasets, analysis of individual reviews can be very thorough but the manual effort to analyse each review is the highest. If the review numbers are greater and new reviews require continuous analysis, more automated techniques are commonly chosen where information extraction is carried out automatically according to a manually encoded set of rules (Abrahams, Jiao, Wang, & Fan, 2012; Hogenboom et al., 2016). Some models have been applied to automate extraction of specific information, such as product defects (Abrahams et al., 2012; Winkler, Abrahams, Gruss, & Ehsani, 2016), reviews with comparisons between products according to their features (Jin, Ji, & Gu, 2016; Yan, Xing, Zhang, & Ma, 2015) or information on which reviews are the most helpful for other customers (Wang, Jiao, Abrahams, Fan, & Zhang, 2013). Those automation methods can produce highly interpretable, concise summaries and offer easily understandable methodologies (Hogenboom et al., 2016). On the other hand, they require significant effort put into customising each model. A model with manually selected information filtering rules may not work when applied reviews written in another subject domain or reviews of authors who use a different choice of vocabulary (Hogenboom et al., 2016; Yan et al., 2015). Therefore, if those automation methods are used on very large datasets, it is sometimes not clear if specific areas of feedback have been entirely ignored because the manually labelled training dataset used to create the model did not include specific vocabularies. An alternative to manually set information extraction rules is to use machine learning in the models such as topic modelling. Topic models are able to extract key features from text documents without explicit, manually set rules for information extraction (Blei, Ng, & Jordan, 2003). Machine learning models are also useful because they are capable to adapt to changes in how customers write their feedback (Blei & Lafferty, 2006; Dai & Storkey, 2015) and can use whole datasets to train the model for feature extraction as opposed to reliance on manually labelled training data (Hogenboom et al., 2016). On the other side, machine learning makes model outcomes may not be easily interpretable (ibid.), and may not always be effective at extraction of the desired information from customer feedback (Winkler et al., 2016). Nonetheless, a topic model such as an Latent Dirichlet Allocation (LDA) can be a highly useful tool for finding out which features of a product or service are the most often commented-on according to customers (Blei et al., 2003; Griffiths & Steyvers, 2004), also in case of public primary care services.

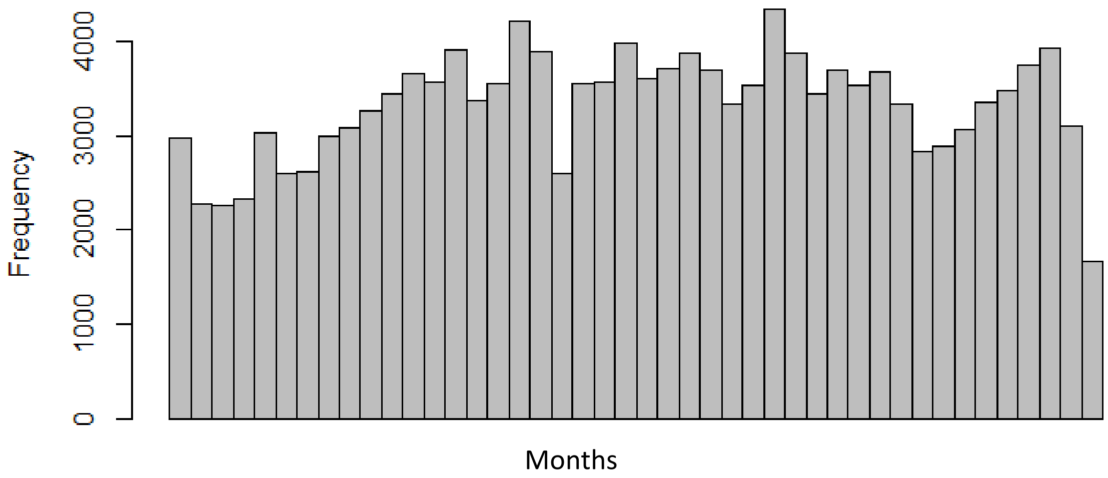
Methods

NHS decision-makers not directly involved with frontline service provision could benefit from analyses of the feedback data that NHS already owns. Customer feedback processed with machine learning models has a potential for supporting decision-making in NHS to generate more value for patients. Therefore, this study investigates the use of LDA topic model to analyse a large body reviews of NHS-funded GP services in England[1]. The data constitute of reviews of GP practices posted from July 2013 to January 2017 about almost 7700 GP practices. Their abundance and availability makes them useful for this study. Anonymous reviewers can post a written comment and answer several Likert-scale statements on their service experience in NHS-funded GP practices. This study involves approximately 89% of all reviews which have been fully filled out. There are over 145 000 of them. Each reviewer posted both a free-text message and Likert-scale answers (from 1 to 5 stars) to each of the survey statements (see figure 1 for a distribution of reviews about GP practices over time). The statements are: 1) “Are you able to get through to the surgery by telephone?”, 2) “Are you able to get an appointment when you want one?”, 3) “Do the staff treat you with dignity and respect?”, 4) “Does the surgery involve you in decisions about your care and treatment?”, 5) “How likely are you to recommend this GP surgery to friends and family if they needed similar care or treatment?”, and 6) “This GP practice provides accurate and up to date information on services and opening hours”. Unfortunately, the review data from NHS Choices are a biased sample of opinion. Older individuals and those who do not use internet are likely under-represented in the dataset. Moreover, anyone can comment on the website and intentionally distort how potential patients evaluate GP practices. Fortunately, however, NHS Choices administrators remove malicious messages from the server manually. Furthermore, NHS Choices staff ensure that unfavourable but legitimate reviews remain in the dataset consistently across England[2].

[1] The data was obtained from NHS Choices, an NHS organisation responsible for handling feedback data. See more at: http://www.nhs.uk/aboutNHSChoices/aboutnhschoices/Pages/what-we-do.aspx,viewed on 1st February 2017

[2] See http://www.nhs.uk/aboutNHSChoices/aboutnhschoices/termsandconditions/Pages/commentspolicy.aspx for further details

Figure 1: Number of reviews monthly from May 2013 to January 2017



Note: The available data cover the period up to 12th January 2017, which is why the last month has fewer reviews than other months

The data processing steps and the LDA topic model have been implemented with 'stm' library available for R programming language[3]. First, each review was tokenized to break down reviews into token lists. For example, a sentence "The doctors were very considerate." was transformed into "The", "doctors", "were", "very", "considerate", "." and word stems were removed, for example so that "doctors" become "doctor". Then, all capital letters were turned into lower case. After that, all non-informative terms such as "very" or "the", numbers, html links and punctuation were removed. The data pre-processing also included removal all tokens which were 1 or 2 characters in length, as well as tokens which occurred fewer than 10 times or more than 100 000 times in the patient reviews. The least and most frequent tokens were removed to reduce the computational power required to carry out LDA topic modelling. Moreover, tokens occurring in most messages or in very few messages are not helpful at identifying key topics in the data. The data cleaning procedure removed 37708 terms, numbers, punctuation types and hyperlinks which occurred 77976 times in GP reviews. The final corpus contained 7660 terms which occurred over 6m times across the dataset.

The pre-processed corpus containing lists of tokens from each GP review was used to compute four LDA topic models. The different topic models were designed to generate 40, 50, 60 and 70 key themes from the GP reviews corpus. Each topic generated with an LDA topic model is a distribution of words which tend to occur together across reviews (Blei et al., 2003). For example, some topics may relate to the words used to thank GPs for their work, while other topics cluster words which tend to co-occur when reviewers complain about an impossibility of scheduling a GP appointment. Choice of the number of topics for the LDA model affects the quality of the output (Blei et al., 2003). If topics are too few, their content gives insight into only very general patterns in text which are not very useful. Too many topics, on the other hand, lead to a large proportion of topics without discernible meaning that can be used. An LDA topic model with an optimal number of topics reveals a large number of insightful patterns in the data without generating many non-meaningful topics. Moreover, models may differ according to their semantic coherence (the rate at which topic's most common words tend to occur together in the same reviews) and exclusivity (the rate at which most common terms are

[3] For a full description of 'stm' library, please visit: https://CRAN.R-project.org/package=stm, viewed on 6th February 2017

exclusive to individual topics) (Roberts, Stewart, & Tingley, 2015). Both metrics are useful guidance of which model to choose (ibid.).

Results

In each case, the model converged in under 100 iterations. The Model with 60 topics was chosen as the best out of the candidate LDA models. The model with 70 topics had a much higher proportion of topics without a discernible meaning related to experience with GP services (see Figure 2). A topic was deemed meaningful if the top 7 most common and distinctive words from a topic were related to an aspect of GP service experience (see Appendix 1 for further details). LDA model with 60 topics offers more detailed insight into GP service experience than the 40 and 50-topic LDA models, while avoiding generation of many meaningless topics as in the case of the model with 70 topics. Another advantage of the model with 60 topics is that it has a superior exclusivity score to alternative models (see Figure 4) which means that its topics overlap semantically relatively less than in the case of other models. The main weakness of the model with 60 topics is that it has the lowest semantic coherence score compared to alternatives (Figure 3).

Figure 2: Proportions of discernible topics for LDA models with 40, 50, 60 and 70 topics

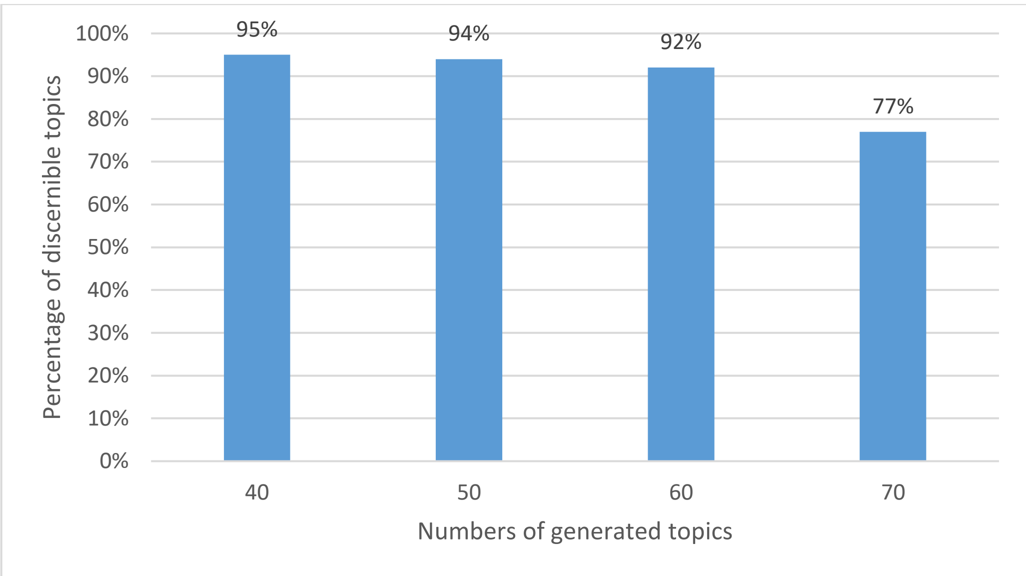


Figure 3: Semantic coherence for LDA models with 40, 50, 60 and 70 topics

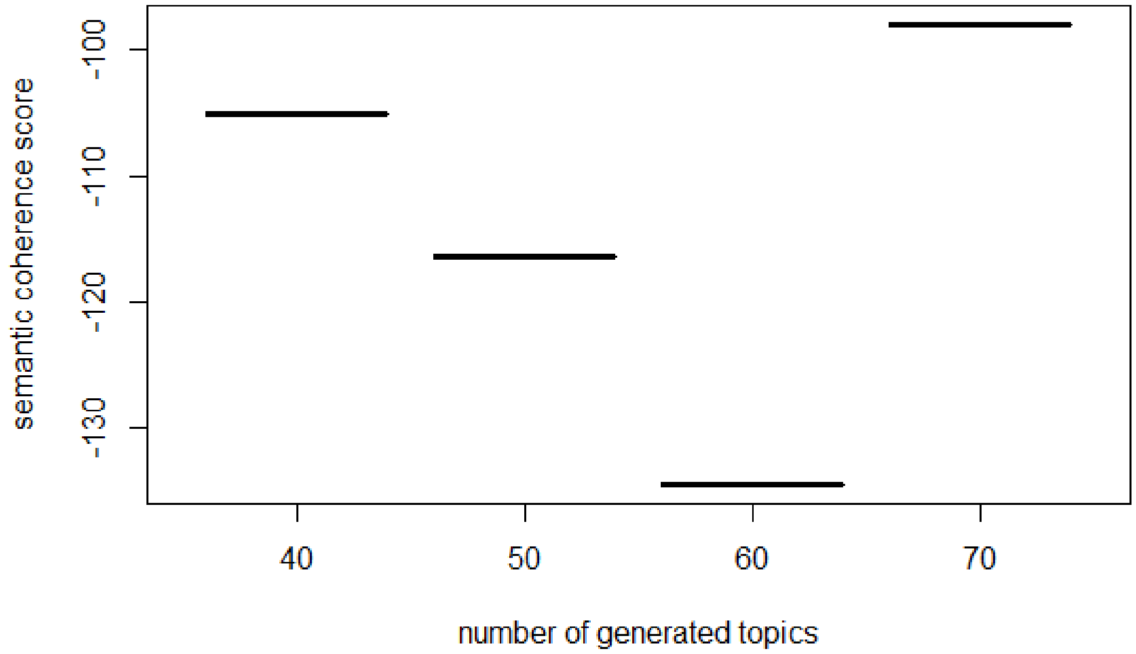
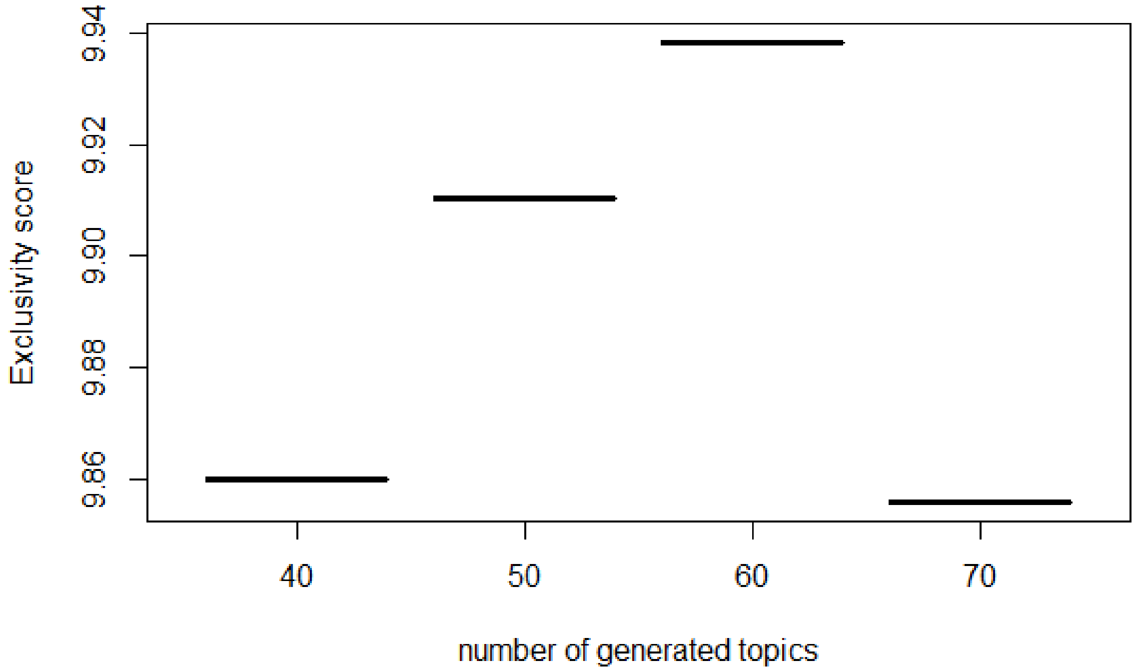


Figure 4: Exclusivity for LDA models with 40, 50, 60 and 70 topics



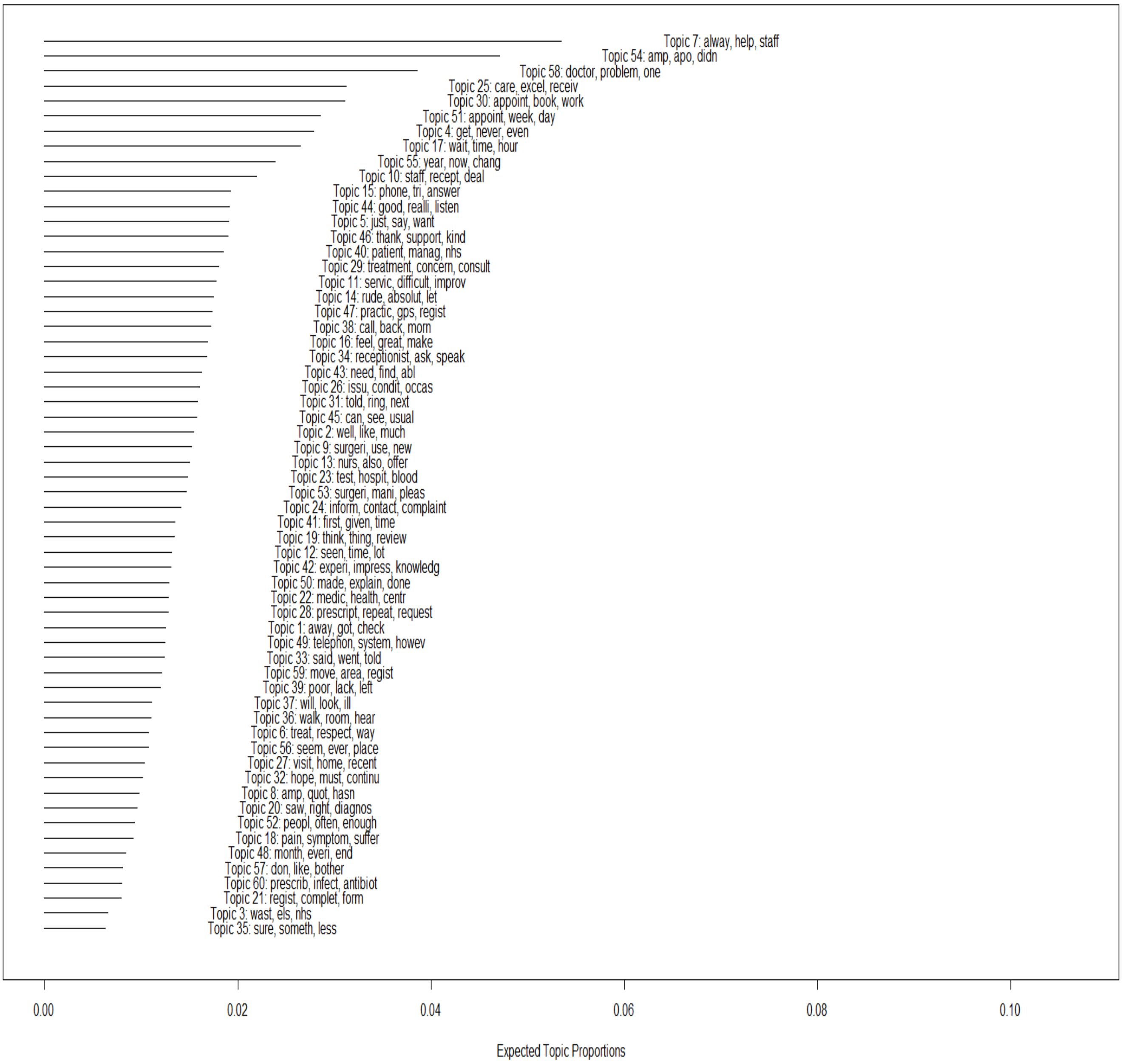
The 60 topics generated with the chosen LDA topic model have been labelled according to the most prominent words in topics listed in Appendix 1 as well as the written reviews which are representative of each topic (see Appendix 2 for details, and Table 1 for a list of topics with labels). The features extracted from text reviews with LDA topic model relate to a range of experiences of patients. The experiences relate to whether GP staff were helpful or not, to cases of perceived miss-diagnosis and difficulties in having a GP appointment. Several topics also offered assessments of the situation of GP services, or were about comparisons between different staff members or between GP practices. Other topics covered evaluations of GP facilities such as toilets and information online about the practice. Finally, several topics (5, 8, 37, 50 and 59) have been generated which relate more to the choices of words used in specific comments than a discernible aspects of GP services. The topics had a varying prevalence across the GP reviews dataset (see Figure 5), from about 5% of tokens in the dataset to under 1% of tokens in the dataset. The topic 7 “friendly doctors” has been the most prevalent of all of them, followed by topic 54 “Unhappy with a quotation”. Topics about the difficulty of scheduling an appointment (4, 17, 30 and 51) also frequently featured in reviews, cumulatively constituting about 8% of all words in reviews.

Table 1: topic labels

Topic 1	Topic 2	Topic 3
Grateful child treated	Helpful practice	Not worth the tax paid
Topic 4	Topic 5	Topic 6
Appointment impossible	[meaning not certain]	Respectful and understanding
Topic 7	Topic 8	Topic 9
Friendly doctors	[citing what GP staff say]	Parking access problem
Topic 10	Topic 11	Topic 12
Receptionists need training	Difficult access	Parents used it much for kids
Topic 13	Topic 14	Topic 15
Star nurse service	Arrogant and unprofessional	Can’t reach on phone
Topic 16	Topic 17	Topic 18
Comforting	Long wait	Suffering
Topic 19	Topic 20	Topic 21
Some good some bad	Right heart diagnosis	Difficult registration
Topic 22	Topic 23	Topic 24
Go extra mile	Difficult referrals	Contact information missing
Topic 25	Topic 26	Topic 27
Excellent care quality	Poor chronic condition treatment	Arranged care at home
Topic 28	Topic 29	Topic 30
Prescription not realised	Prompt treatment	Advanced booking unavailable
Topic 31	Topic 32	Topic 33
Hard to book on phone	Big changes in GP service	Distressing treatment for condition
Topic 34	Topic 35	Topic 36
Situation with receptionists	Unhelpful	Insufficient facilities
Topic 37	Topic 38	Topic 39
[meaning not certain]	Hard to reach on phone	Poor manners
Topic 40	Topic 41	Topic 42
patient engagement	Advising others	Competent and impressive
Topic 43	Topic 44	Topic 45
Surprising service	Nice and clean	Usually difficult appointments
Topic 46	Topic 47	Topic 48

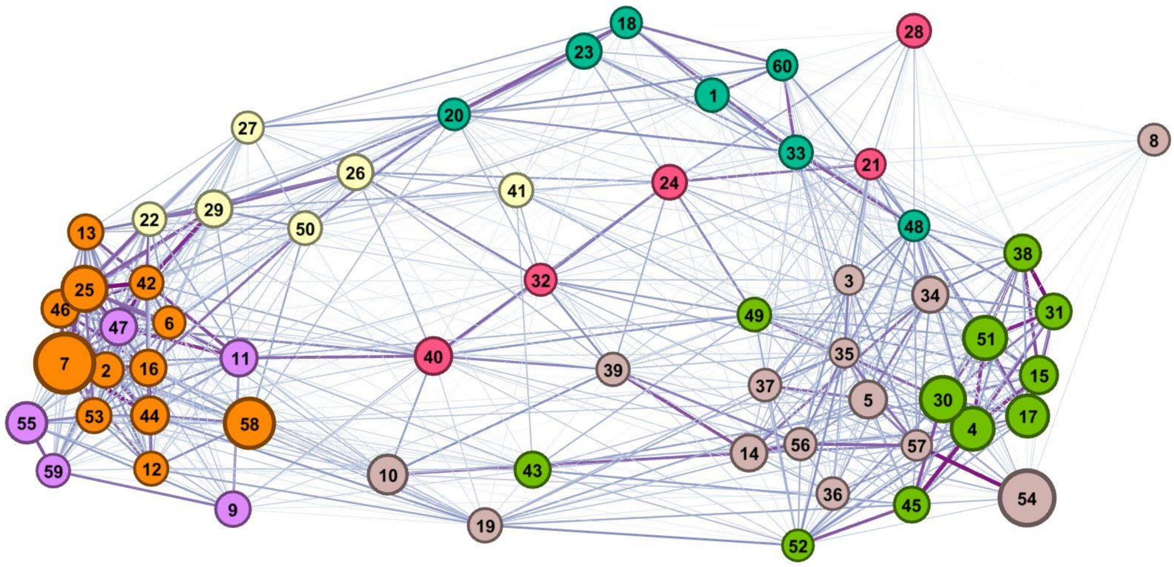
Saying thanks	Impressive practice	Bad experience
Topic 49	Topic 50	Topic 51
Ineffective booking system	Sharing feelings	Emergencies without appointment
Topic 52	Topic 53	Topic 54
Healthcare system not good	Pleasant experience	Unhappy with a quotation
Topic 55	Topic 56	Topic 57
Visible changes	The worst ever	annoying
Topic 58	Topic 59	Topic 60
One doctor is unique	Comparing GP practices	Maybe misdiagnosis, ear

Figure 5: Shares of reviews according to 60 topics from the LDA model



Topics can also be compared with regard to their similarity to one another. It is assumed that two topics are similar if the choice of vocabulary they represent is similar, and they are very different if there are few common words present in both of them. Figure 6 represents the relative similarities between topics portrayed on a two-dimensional plane. The distances between topics have been computed with a cosine similarity scores calculated for each topic. The result was a slightly elongated mapping of topics which broadly cluster into 2 groups, one on the left and one on the right hand side of the graph. A closer inspection of figure 6 reveals that the greatest distance occurs between, on one hand, topics with positive evaluations of GP services, such as "Helpful practice", "saying thanks", "friendly doctors", "excellent care quality" and "Comforting" (left) and, on the other hand, topics with reviewers finding it hard to use GP services, such as "hard to reach on phone", "hard to book on phone", "long wait", "can't reach on phone" and "appointment impossible" (right). Patients unable to reach their GP service were least likely to express positive feelings about their GP service experience. The middle ground with topics "advising others" (41), "big changes in GP service" (32) and "poor manners" (39) suggests that reviewers critically evaluated the service and wanted to share their experience and observations. The comparison of top and bottom sides of the graph, in turn, tend to indicate differences in writing style. For example, topics "difficult referrals" (23) and "arranged care at home" (27) on the top tended to have been written in a very factual language, whereas topics on the bottom such as "receptionists need training" (10), "surprising service" (43) and "usually difficult appointments" (45) tended to have been written in a highly emotive language (please refer to Appendix 2 for text review samples).

Figure 6: Two-dimensional map of 60 topics generated with the LDA model



Topic prevalence in GP reviews can also be related to how reviewers rate their GP service experience in Likert-scale numeric responses. In order to evaluate the relationship, the proportion presence of each topic in each review was used as dependent variable, and the star ratings accompanying each of the 6 survey statements in each review were used as independent variables. Figures 5-16 feature linear correlations between each of the six independent variables and a) a sample of topics intuitively considered as related to the independent variable, and b) a sample of topics intuitively considered as unrelated to the independent variables. Pairs of figures 7 & 8, 9 & 10, 11 & 12 as well as 13 & 14 indicate that indeed the intuitively selected relevant topic proportions present in reviews tend to be correlated to the Likert-scale responses on similar subjects, whereas topics considered as unrelated to star ratings on specific survey questions tended to have near zero coefficients. On the other hand, the pattern of correlation of intuitively relevant topics generated with LDA with star ratings was not as clearly evident in case of survey statements “How likely are you to recommend this GP surgery to friends and family if they needed similar care or treatment?” and “This GP practice provides accurate and up to date information on services and opening hours”. In the case of the former statement, the intuitive understanding of the relationship between topics’ meaning and star ratings was still present although it was weak. Presence of topics “the worst ever” (56), “annoying” (57) and “bad experience” (48) tended to be smaller for reviews with higher star ratings, while the topics “go extra mile” (22) and “respectful and understanding” (6) were less present in reviews with low star ratings (see Figure 13). The star ratings for the latter statement were similarly weakly correlated with the intuitively selected topics.

Figure 7: Proportional presence of five LDA topics related to the question "Are you able to get through to the surgery by telephone?"

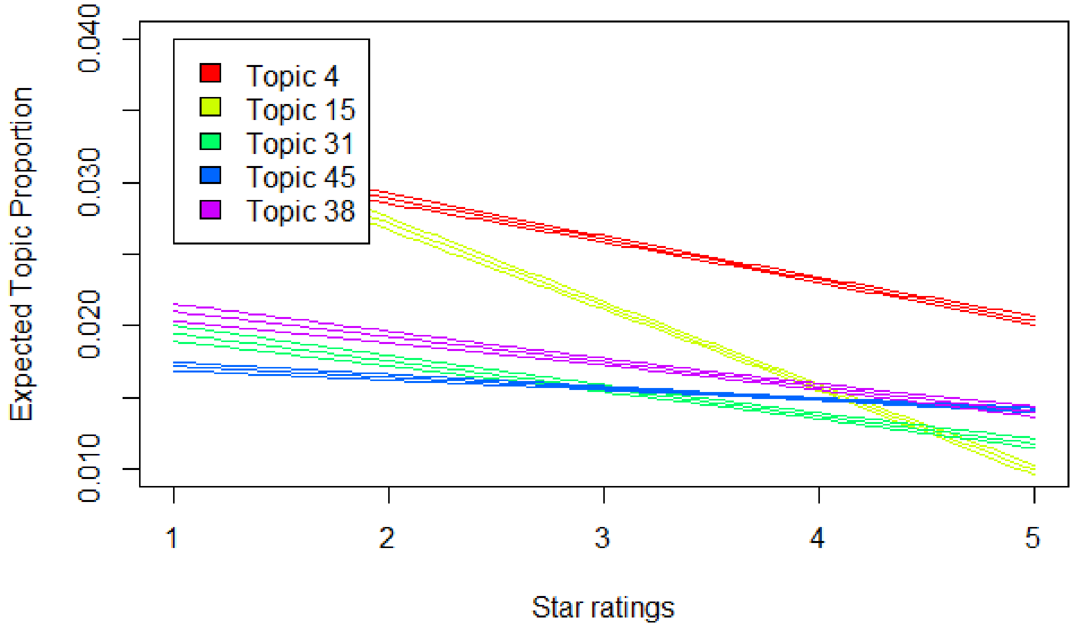


Figure 8: Proportional presence of five LDA topics not related to the question "Are you able to get through to the surgery by telephone?"

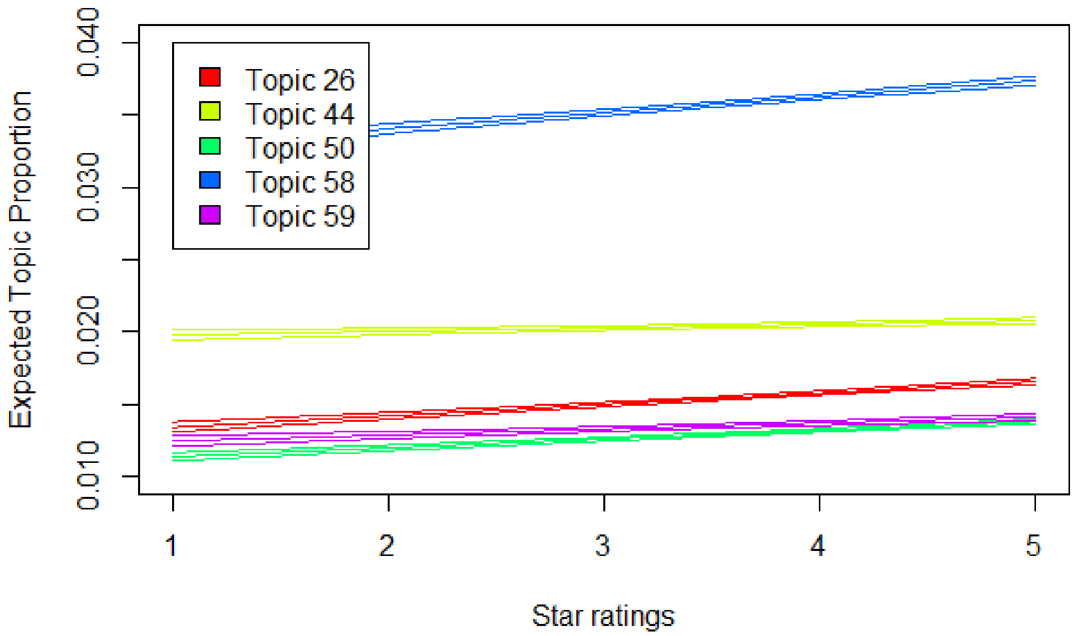


Figure 9: Proportional presence of five LDA topics related to the question "Are you able to get an appointment when you want one?"

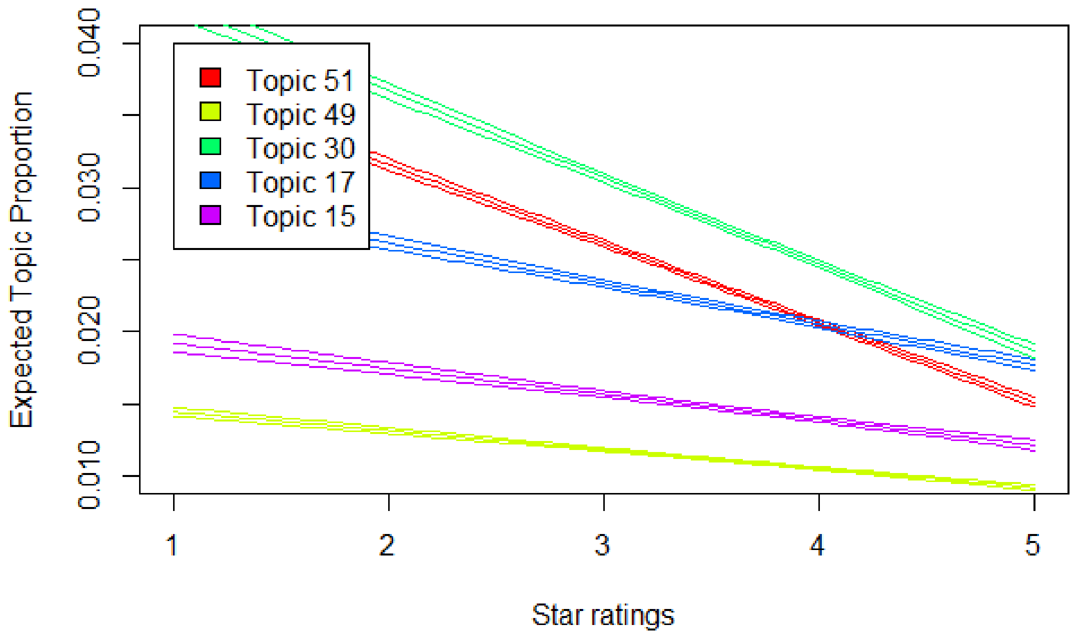


Figure 10: Proportional presence of five LDA topics not related to the question "Are you able to get an appointment when you want one?"

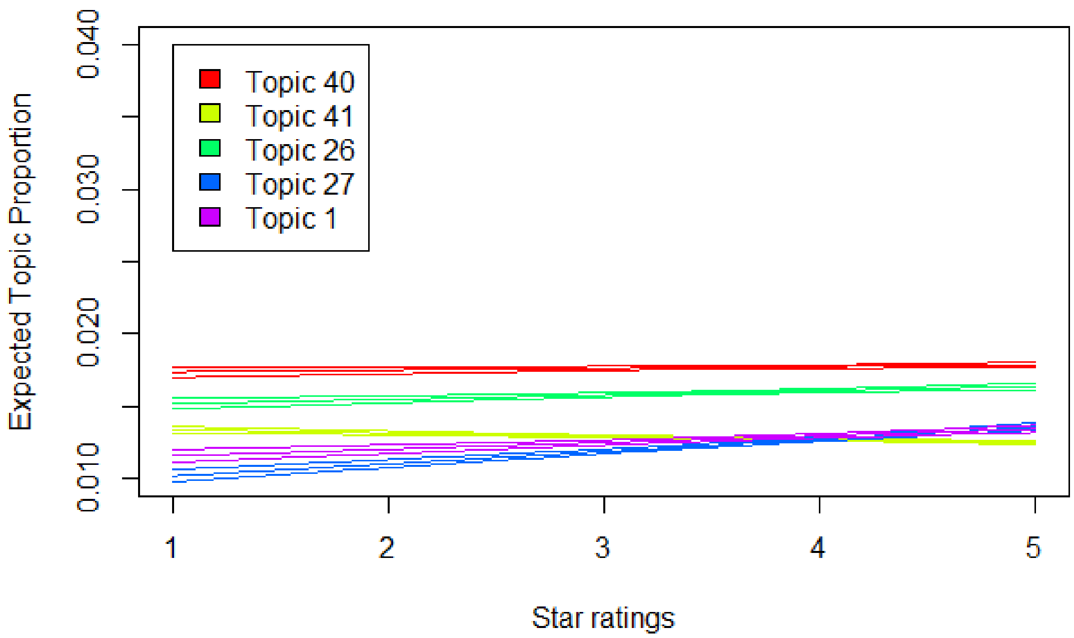


Figure 11: Proportional presence of five LDA topics related to the question "Do the staff treat you with dignity and respect?"

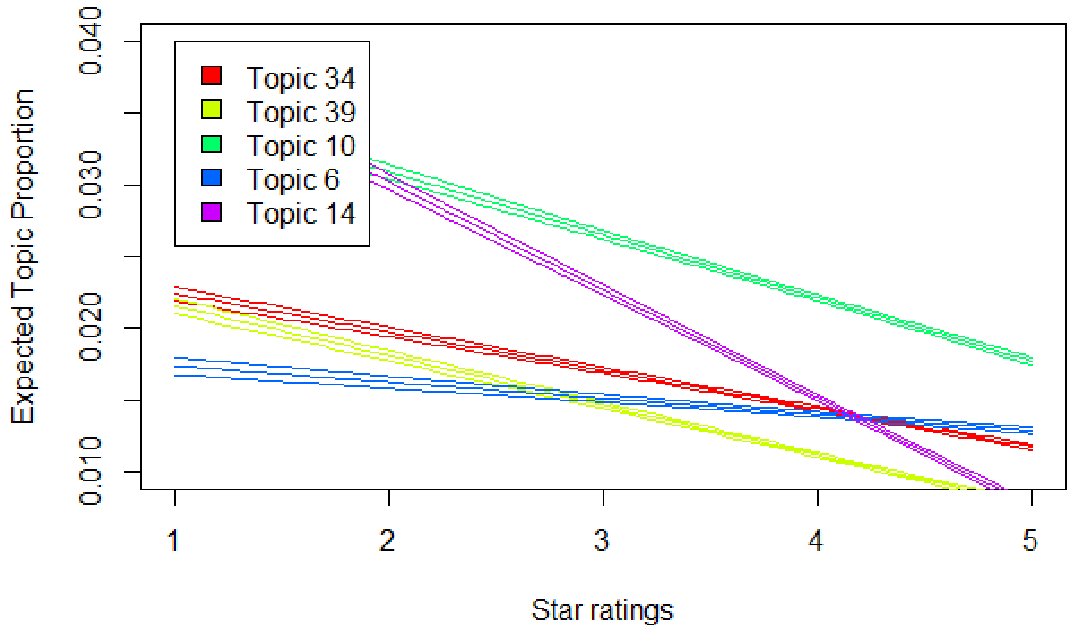


Figure 12: Proportional presence of five LDA topics not related to the question "Do the staff treat you with dignity and respect?"

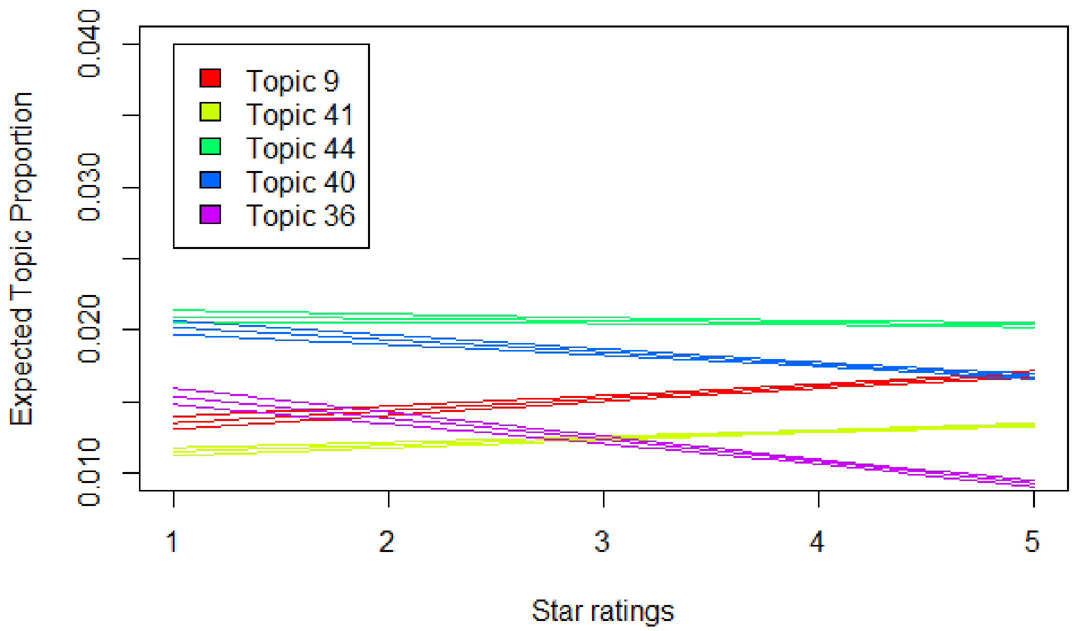


Figure 13: Proportional presence of five LDA topics related to the question "Does the surgery involve you in decisions about your care and treatment?"

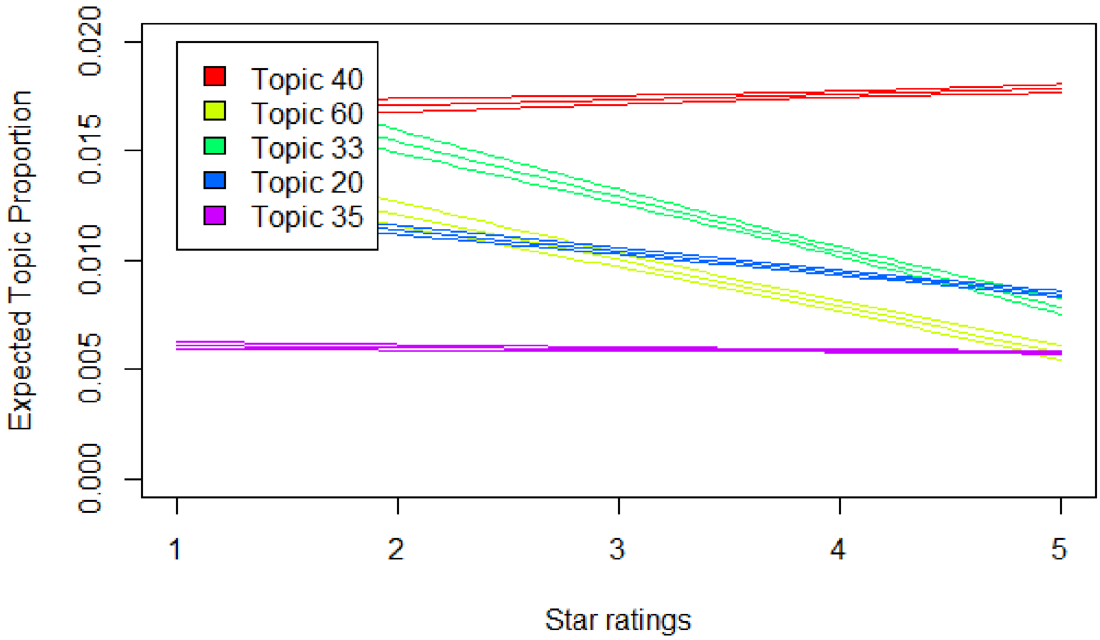


Figure 14: Proportional presence of five LDA topics not related to the question "Does the surgery involve you in decisions about your care and treatment?"

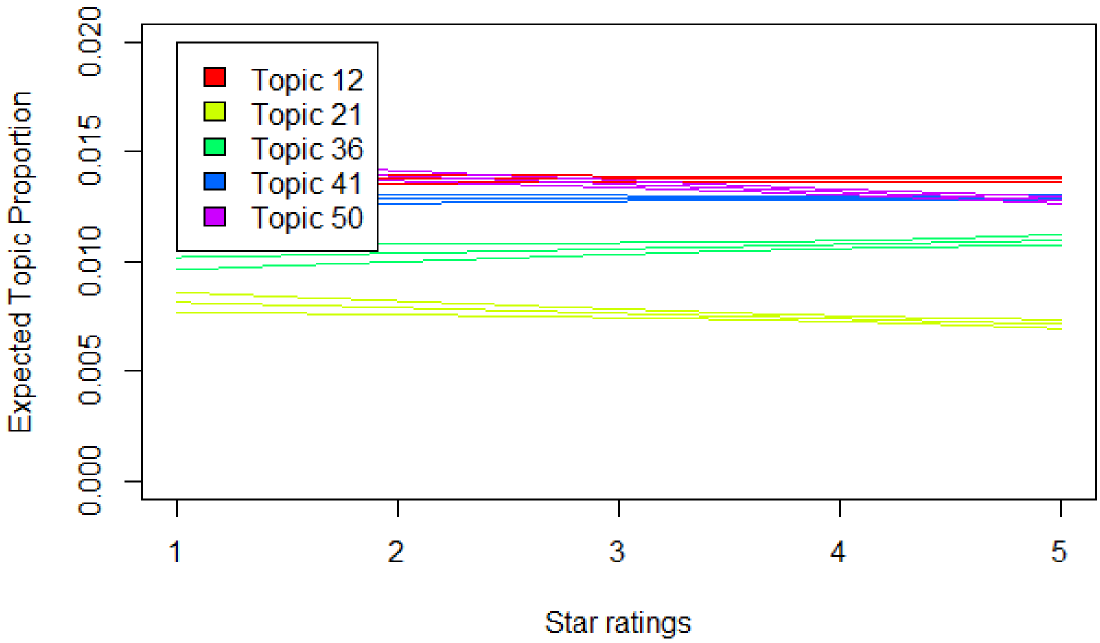


Figure 15: Proportional presence of five LDA topics related to the question "How likely are you to recommend this GP surgery to friends and family if they needed similar care or treatment?"

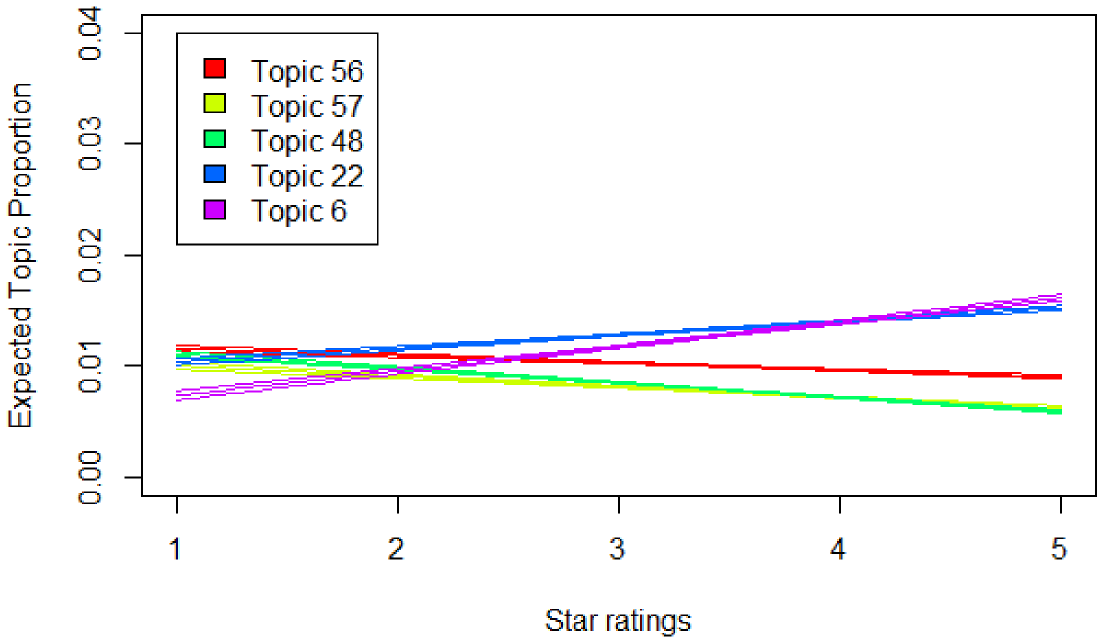


Figure 16: Proportional presence of five LDA topics not related to the question "How likely are you to recommend this GP surgery to friends and family if they needed similar care or treatment?"

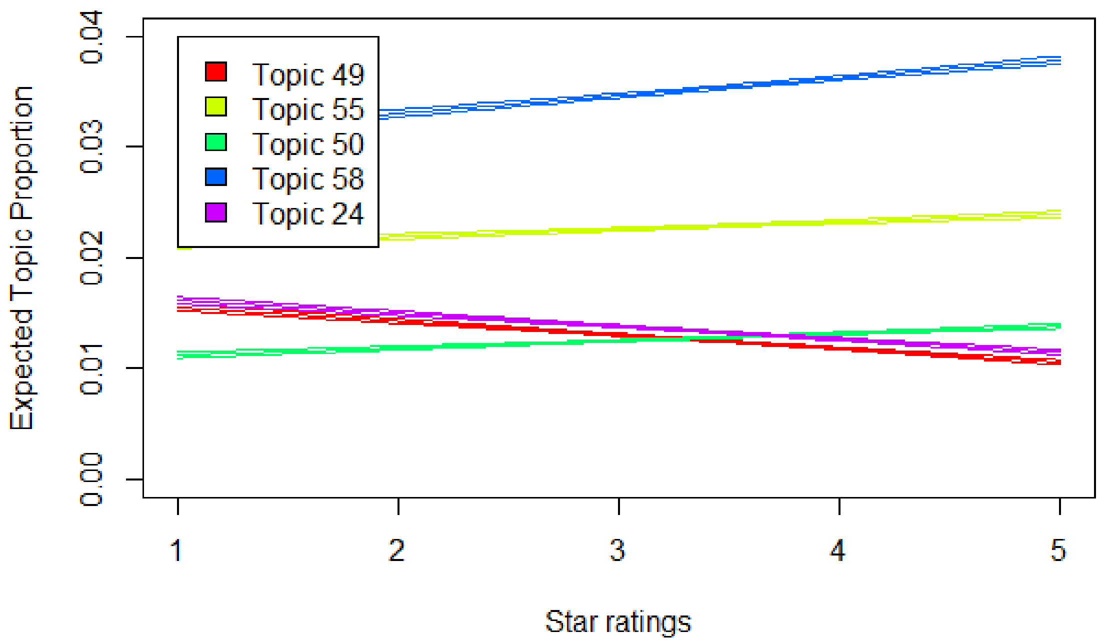


Figure 17: Proportional presence of five LDA topics related to a statement "This GP practice provides accurate and up to date information on services and opening hours"

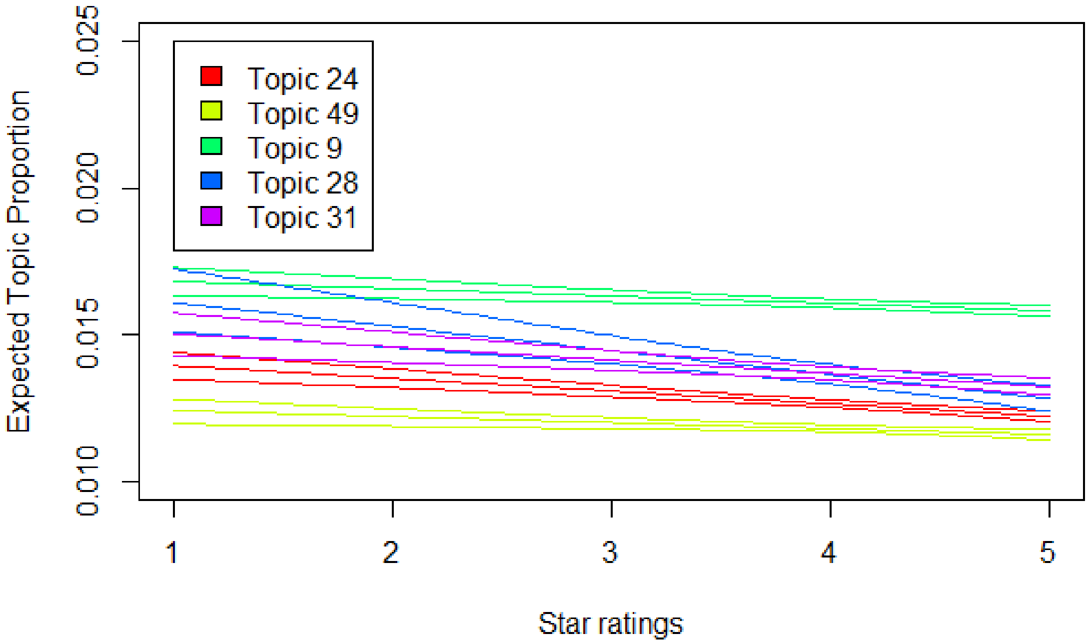
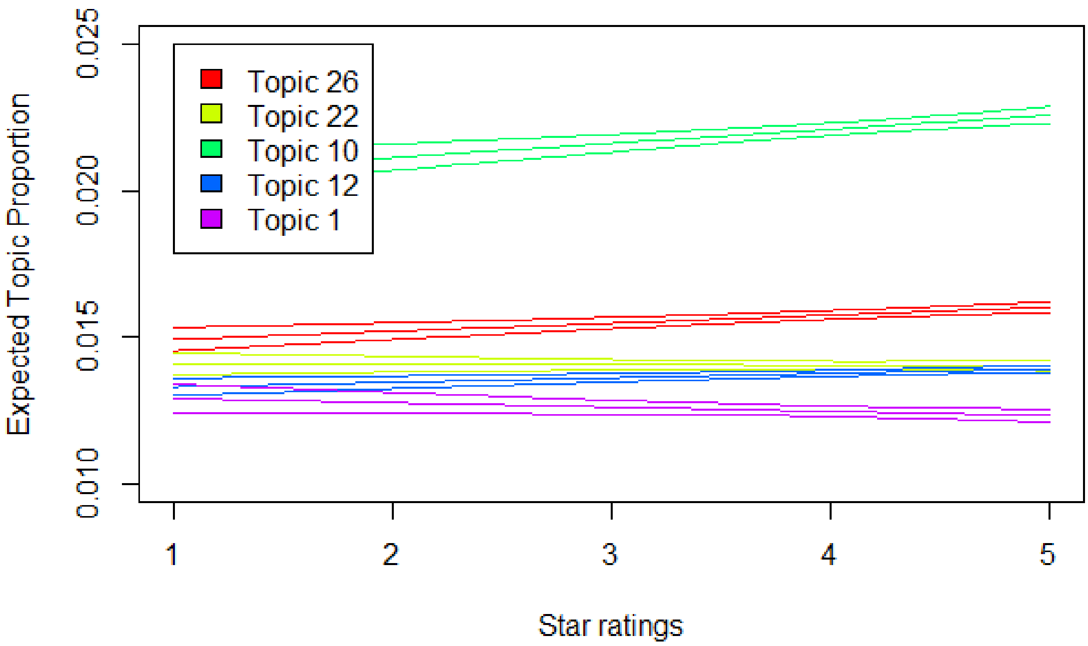


Figure 18: Proportional presence of five LDA topics not related to a statement "This GP practice provides accurate and up to date information on services and opening hours"



Discussion and conclusion

LDA topic model outcomes analysed in this study offer a broad range of insights into the experiences patients have with GP services. The results constitute evidence that topic models are useful for summarising large numbers of written reviews. The outcomes of topic modelling are similarly complex to conclusions from qualitative studies of similar datasets (e.g. Lopez et al., 2012). Moreover, topic models can yield more insight than alternative methods of feature extraction such as sentiment model often used for processing of written reviews (James et al., 2017). LDA extracts a number of themes from the text reviews as they occur in the data while sentiment analysis can only extract individual themes from reviews along subjectively selected and not very transparent criteria (ibid.).

Topic models constructed from online reviews could be helpful at guiding change in NHS on national and regional level, as opposed to supporting change only on a local level. For example, NHS could use topic modelling to identify successful GP practices by filtering the data to look at the most impressive GP practices across England, and learn from what is common to those practices. Other uses of topic models can include analyses of key challenges facing the NHS which could be overcome nationally in a more effective manner than locally. For example, this study suggests many patients are confused and frustrated by the difficulty in making GP appointments. Modelling outcomes suggest that a nation-wide online booking system which GP practices and patients can use to transparently manage GP appointments could help. Patients could choose to attend practices with a GP lower appointment load or different opening hours if they prefer so at a given moment. Moreover, topic model insights suggest that patients seeking repeat prescriptions for long-term conditions could be treated in a different manner from others to reduce unnecessary disruption in their lives, and that lack of a nation-wide automated system for passing on prescriptions on to chemists causes problems for some patients. Apart from that, in addition to benefitting NHS decision-makers, topic models can help inform research into public preferences with regard to NHS services and can help inform public about the current NHS challenges in terms of patient satisfaction.

Unfortunately, the validity and reliability of topic model outcomes is limited by the fact that most patients do not post reviews online. On average, GP practices received fewer than 20 reviews over a period of three and a half years. GP practice-level comparisons based on the topic content of reviews are not feasible given the limited size of the dataset, but comparisons between larger NHS administrative areas such as Clinical Commissioning Groups or NHS Regions could help document the impact of mid-level NHS administration on GP performance. Another problem is that the biases in the sample of patient experiences analysed with the LDA topic model are unknown. For example, studies suggest the bias in online reviews of services is very dependent on how feedback is collected (Xiang, Du, Ma, & Fan, 2017). Online reviewers also tend to be more positive-sounding when they post reviews online which can be read by others, compared to when offline reviews are collected (Gao, Greenwood, Agarwal, & McCullough, 2015). Therefore, it is advisable to compare the LDA topic model results obtained from anonymous GP reviews with a representative and systematic survey of patients' opinion about their GP service experience. The comparison could help establish how representative are the outcomes of topic modelling. In the context of NHS, GP Patient Survey is at present the most systematic and regularly collected opinion survey about GP services in England (Cowling, Harris, & Majeed, 2015) and could be used for making such a comparison.

In summary, public management of NHS funded GP services can benefit from introduction of more machine learning algorithms to support organisational learning at a national and regional level. Topic model machine learning algorithms can be used to process very large numbers of patient reviews into insights which are relatively complex but at the same time also easy to understand and actionable. The opportunity to use machine learning to process online reviews of patients is especially applicable because the data are already available, and can offer a near real-time, low cost substitute to patient surveys.

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Appendix 1: LDA models' topic lists

Topics generated with each LDA topic model have been highlighted in yellow if they were deemed not meaningfully related to GP service experience based on inspection of the words representing it. Each topic (a probability distribution over words) is represented with 2 lists of words:

- Highest Prob: the words within the topic which have the highest frequency of occurring in it
- FREX: the words which are exclusive to the topic with the highest probabilities of occurring in it. I.e these are the words that distinguish topics. FREX scores for words are a harmonic mean of rank by probability within the topic (frequency) and rank by distribution of topic given word (exclusivity)

Table of Contents

LDA topic model with 40 topics

```
Topic 1 Top Words:
         Highest Prob: told, got, morn, rang, next, min, week
         FREX: appt, monday, friday, tuesday, thursday, rang, wednesday
Topic 2 Top Words:
         Highest Prob: feel, issu, health, felt, listen, life, understand
         FREX: mental, depress, felt, life, uncomfort, fear, languag
Topic 3 Top Words:
         Highest Prob: will, time, walk, open, clinic, surgeri, get
         FREX: flu, jab, saturday, clinic, asthma, smoke, full
Topic 4 Top Words:
         Highest Prob: doctor, problem, see, give, time, everi, know
         FREX: rest, boy, problem, wood, solv, mind, doctor
Topic 5 Top Words:
         Highest Prob: thank, much, doctor, kind, surgeri, enough, mani
         FREX: thank, troubl, bless, prais, amaz, sincer, big
Topic 6 Top Words:
         Highest Prob: call, receptionist, back, ask, speak, said, someon
         FREX: call, spoke, nobodi, hung, lunch, back, speak
Topic 7 Top Words:
         Highest Prob: one, time, can, need, howev, doctor, surgeri
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FREX: drs, prefer, odd, popular, donâ, load, bit
Topic 8 Top Words:
Highest Prob: get, abl, use, surgeri, appoint, usual, within
FREX: abl, usual, conveni, unlik, rare, within, use
Topic 9 Top Words:
Highest Prob: staff, help, alway, recept, best, great, polit
FREX: extra, mile, help, best, accommod, accomod, grove
Topic 10 Top Words:
Highest Prob: phone, get, tri, ring, answer, line, appoint
FREX: engag, line, answer, ring, hold, phone, messag
Topic 11 Top Words:
Highest Prob: like, peopl, talk, way, recept, staff, one
FREX: abrupt, spoken, talk, favour, loud, air, miser
Topic 12 Top Words:
Highest Prob: apo, don, know, amp, just, want, bother
FREX: don, shouldn, horrend, clue, bother, sarcast, sigh
Topic 13 Top Words:
Highest Prob: surgeri, experi, recent, extrem, also, short, found
FREX: south, east, short, villag, comparison, sadden, defin
Topic 14 Top Words:
Highest Prob: amp, apo, couldn, doesn, wouldn, just, hasn
FREX: wouldn, amp, hasn, doesn, couldn, apo, weren
Topic 15 Top Words:
Highest Prob: week, two, month, last, anoth, still, three
FREX: three, holiday, text, two, six, juli, promis
Topic 16 Top Words:
Highest Prob: hospit, refer, referr, prescrib, symptom, diagnos, treatment
FREX: dress, skin, wound, weight, diagnos, discharg, diseas
Topic 17 Top Words:
Highest Prob: practic, patient, servic, provid, gps, care, standard
FREX: consist, abil, qualiti, clinician, maintain, standard, valu
Topic 18 Top Words:
Highest Prob: care, medic, receiv, support, team, centr, health
FREX: dedic, ensur, attent, team, throughout, outstand, proactiv
Topic 19 Top Words:
Highest Prob: prescript, medic, repeat, request, order, pharmaci, surgeri
FREX: prescript, repeat, collect, chemist, order, readi, pharmaci
Topic 20 Top Words:
Highest Prob: appoint, book, day, system, avail, get, work
FREX: book, advanc, pre, system, imposs, avail, appoint
Topic 21 Top Words:
Highest Prob: wait, time, minut, hour, long, late, run
FREX: wait, late, averag, room, run, sit, longer
Topic 22 Top Words:
Highest Prob: test, blood, result, pain, went, done, check
FREX: blood, test, sampl, urin, smear, mri, lump
Topic 23 Top Words:
Highest Prob: surgeri, also, park, hous, well, door, main
FREX: park, car, space, build, locat, plenti, small
Topic 24 Top Words:
Highest Prob: even, time, just, els, wast, anoth, get
FREX: els, somewher, useless, pill, hang, wast, contracept
Topic 25 Top Words:
Highest Prob: year, surgeri, move, regist, sinc, doctor, area
FREX: move, sinc, join, children, catchment, young, femal
Topic 26 Top Words:
Highest Prob: inform, complet, form, name, record, detail, address
FREX: fill, form, registr, address, incorrect, record, websit
Topic 27 Top Words:
Highest Prob: patient, manag, review, servic, poor, staff, practic
FREX: fund, govern, public, client, survey, negat, manag
Topic 28 Top Words:
Highest Prob: consult, requir, condit, discuss, advic, medic, number
FREX: activ, resourc, group, increas, difficulti, addit, term
Topic 29 Top Words:
Highest Prob: recommend, excel, treat, famili, high, treatment,

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        care
        FREX: digniti, respect, utmost, hesit, high, humour, recommend
Topic 30 Top Words:
        Highest Prob: rude, receptionist, recept, bad, attitud, unhelp,
        seem
        FREX: unhelp, rude, attitud, uncar, unfriend, shout, disrespect
Topic 31 Top Words:
        Highest Prob: friend, alway, nurs, happi, found, surgeri, effici
        FREX: welcom, pleasant, friend, warm, eas, cheer, effici
Topic 32 Top Words:
        Highest Prob: appoint, need, emerg, get, see, urgent, offer
        FREX: urgent, routin, emerg, triag, slot, non, appoin
Topic 33 Top Words:
        Highest Prob: refus, babi, child, nhs, check, privat, note
        FREX: pay, babi, charg, tax, vaccin, privat, insur
Topic 34 Top Words:
        Highest Prob: can, apo, get, amp, isn, haven, won
        FREX: haven, won, isn, aren, pretti, unless, luck
Topic 35 Top Words:
        Highest Prob: surgeri, find, seen, good, doctor, time, new
        FREX: choos, handi, choic, suit, central, easier, belt
Topic 36 Top Words:
        Highest Prob: visit, nurs, doctor, home, explain, saw, advic
        FREX: dad, carer, green, hall, west, visit, brother
Topic 37 Top Words:
        Highest Prob: work, good, difficult, peopl, sometim, hard, think
        FREX: hard, sometim, moan, perfect, keep, difficult, tend
Topic 38 Top Words:
        Highest Prob: never, even, just, one, ever, place, absolut
        FREX: absolut, terribl, unsympathet, apt, rid, everytim, unbeliev
Topic 39 Top Words:
        Highest Prob: concern, made, manner, regard, question, person,
        show
        FREX: bedsid, nuisanc, natur, deepli, lifestyl, judgement, vulner
Topic 40 Top Words:
        Highest Prob: quot, amp, said, didn, ask, wasn, went
        FREX: quot, ear, didn, hadn, temperatur, midwif, deaf
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LDA topic model with 50 topics

```
Topic 1 Top Words:
        Highest Prob: got, today, rang, away, daughter, advis, son
        FREX: appt, son, daughter, rang, vaccin, today, app
Topic 2 Top Words:
        Highest Prob: hospit, consult, follow, treatment, home, wife,
        husband
        FREX: cancer, immedi, discharg, heart, wife, ambul, stage
Topic 3 Top Words:
        Highest Prob: open, place, even, either, close, wors, joke
        FREX: close, lunch, rubbish, luck, break, cut, chanc
Topic 4 Top Words:
        Highest Prob: nurs, also, made, attend, clinic, explain, first
        FREX: clinic, attend, jab, flu, dress, wound, nurs
Topic 5 Top Words:
        Highest Prob: doctor, good, time, problem, never, sometim, one
        FREX: fault, good, sometim, everybodi, moan, problem, coupl
Topic 6 Top Words:
        Highest Prob: thank, support, kind, team, enough, appreci, wonder
        FREX: thank, prais, support, team, grate, extra, gratitud
Topic 7 Top Words:
        Highest Prob: get, can, never, tri, ridicul, unless, lucki
        FREX: nightmar, ridicul, get, can, appoin, pointless, guarante
Topic 8 Top Words:
        Highest Prob: time, wait, hour, seen, minut, late, long
        FREX: wait, hour, late, half, arriv, minut, min
Topic 9 Top Words:
        Highest Prob: use, difficult, usual, often, although, general,
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also
FREX: park, build, larg, often, space, although, difficult
Topic 10 Top Words:
Highest Prob: appoint, day, book, week, avail, emerg, urgent
FREX: advanc, book, emerg, pre, appoint, urgent, ahead
Topic 11 Top Words:
Highest Prob: staff, help, recept, polit, extrem, done, well
FREX: help, polit, accomod, staff, upmost, woodland, reccomend
Topic 12 Top Words:
Highest Prob: say, come, want, leav, one, sort, hope
FREX: say, ive, soon, leav, moment, appoit, come
Topic 13 Top Words:
Highest Prob: call, told, back, ring, morn, tri, next
FREX: ring, morn, tomorrow, afternoon, call, next, back
Topic 14 Top Words:
Highest Prob: recept, staff, person, patient, attitud, member, speak
FREX: front, desk, train, custom, confidenti, abrupt, wit
Topic 15 Top Words:
Highest Prob: actual, someon, enough, ill, els, one, might
FREX: els, somewher, mayb, anywher, annoy, might, battl
Topic 16 Top Words:
Highest Prob: feel, realli, listen, much, understand, love, nice
FREX: nice, love, rush, drs, realli, feel, listen
Topic 17 Top Words:
Highest Prob: now, visit, last, month, two, year, three
FREX: last, four, replac, reli, begin, visit, now
Topic 18 Top Words:
Highest Prob: said, ask, told, went, infect, gave, came
FREX: antibiot, throat, cough, infect, tonsil, fever, went
Topic 19 Top Words:
Highest Prob: medic, without, due, check, prescrib, partner, take
FREX: asthma, weight, histori, control, side, reaction, dose
Topic 20 Top Words:
Highest Prob: inform, complet, despit, note, form, fact, record
FREX: form, registr, record, state, fail, despit, complet
Topic 21 Top Words:
Highest Prob: chang, new, experi, recent, practic, differ, one
FREX: experi, new, chang, previous, sad, star, join
Topic 22 Top Words:
Highest Prob: care, receiv, treatment, attent, concern, particular, reassur
FREX: attent, exemplari, consider, utmost, genuin, ensur, reassur
Topic 23 Top Words:
Highest Prob: receptionist, rude, one, absolut, ever, unhelp, never
FREX: worst, unhelp, spoken, patronis, uncar, rude, terribl
Topic 24 Top Words:
Highest Prob: patient, gps, may, improv, rather, expect, face
FREX: resourc, perman, part, meet, vari, survey, appear
Topic 25 Top Words:
Highest Prob: system, work, abl, telephon, offer, servic, onlin
FREX: system, triag, telephon, conveni, option, onlin, worker
Topic 26 Top Words:
Highest Prob: doctor, see, walk, one, anoth, even, want
FREX: dont, cant, see, that, wont, doesnt, apoint
Topic 27 Top Words:
Highest Prob: just, like, know, look, bad, thing, someth
FREX: someth, god, just, bad, look, stuff, right
Topic 28 Top Words:
Highest Prob: prescript, repeat, request, surgeri, order, pharmaci, sign
FREX: prescript, repeat, collect, chemist, order, readi, request
Topic 29 Top Words:
Highest Prob: apo, didn, couldn, even, wasn, wouldn, haven
FREX: wasn, couldn, didn, wouldn, hadn, haven, shouldn
Topic 30 Top Words:
Highest Prob: will, make, sure, take, gone, miss, one
FREX: sure, will, hit, downhil, plus, anybodi, harder
Topic 31 Top Words:

Highest Prob: pain, sever, refer, referr, symptom, suffer, caus
FREX: physio, specialist, relief, mri, skin, killer, injuri
Topic 32 Top Words:
Highest Prob: phone, answer, line, surgeri, busi, call, speak
FREX: answer, hold, phone, queue, line, hang, messag
Topic 33 Top Words:
Highest Prob: manag, nhs, review, poor, complaint, complain, read
FREX: review, negat, feedback, manag, complaint, govern, page
Topic 34 Top Words:
Highest Prob: year, regist, move, sinc, centr, area, medic
FREX: london, street, north, citi, east, green, hall
Topic 35 Top Words:
Highest Prob: practic, provid, patient, continu, level, requir, experienc
FREX: group, maintain, encourag, standard, qualiti, highest, provis
Topic 36 Top Words:
Highest Prob: servic, excel, profession, high, effici, well, impress
FREX: excel, effici, courteous, aspect, knowledg, profession, compet
Topic 37 Top Words:
Highest Prob: time, end, wast, least, almost, pay, everi
FREX: pay, money, wast, tax, least, expens, spend
Topic 38 Top Words:
Highest Prob: friend, great, receptionist, fantast, pleasant, welcom, brilliant
FREX: friend, welcom, pleasant, warm, fantast, atmospher, clean
Topic 39 Top Words:
Highest Prob: surgeri, recommend, treat, famili, respect, anyon, definit
FREX: digniti, recommend, hesit, lane, respect, definit, villag
Topic 40 Top Words:
Highest Prob: room, old, turn, babi, child, sick, door
FREX: child, seat, babi, chair, kid, dirti, toddler
Topic 41 Top Words:
Highest Prob: need, surgeri, occas, make, mind, rare, set
FREX: need, whatev, suitabl, merg, patent, hill, set
Topic 42 Top Words:
Highest Prob: test, blood, result, letter, done, week, sent
FREX: test, blood, result, sampl, midwif, smear, pregnanc
Topic 43 Top Words:
Highest Prob: alway, best, found, year, happi, doctor, seen
FREX: happi, alway, best, fresh, super, found, easi
Topic 44 Top Words:
Highest Prob: work, seem, find, peopl, think, keep, hard
FREX: hard, keep, quit, find, rememb, backward, think
Topic 45 Top Words:
Highest Prob: amp, apo, isn, can, one, enough, nan
FREX: isn, apo, amp, nan, gold, fanci, brandon
Topic 46 Top Words:
Highest Prob: health, issu, condit, serious, discuss, concern, long
FREX: issu, mental, term, health, ongo, resolv, ailment
Topic 47 Top Words:
Highest Prob: don, apo, tell, doesn, amp, want, know
FREX: don, doesn, won, aren, anymor, damn, clue
Topic 48 Top Words:
Highest Prob: littl, ill, show, mother, worri, age, unwel
FREX: mum, mother, elder, parent, dad, born, unwel
Topic 49 Top Words:
Highest Prob: way, mani, patient, believ, wish, practis, well
FREX: practis, doubt, benefit, countri, temporari, true, world
Topic 50 Top Words:
Highest Prob: amp, quot, repli, ear, ask, well, pill
FREX: quot, contracept, syring, googl, deaf, ear, implant

LDA topic model with 60 topics

```
Topic 1 Top Words:
        Highest Prob: away, got, check, old, took, daughter, son
        FREX: babi, son, vaccin, daughter, straight, immunis, inject
Topic 2 Top Words:
        Highest Prob: well, like, much, better, keep, noth, brilliant
        FREX: much, troubl, thankyou, big, guy, brilliant, awesom
Topic 3 Top Words:
        Highest Prob: wast, els, nhs, instead, privat, pay, free
        FREX: pay, money, tax, somewher, privat, insur, wast
Topic 4 Top Words:
        Highest Prob: get, never, even, imposs, one, though, almost
        FREX: imposs, get, terribl, constant, almost, nightmar, luck
Topic 5 Top Words:
        Highest Prob: just, say, want, know, give, come, dont
        FREX: dont, that, isnt, there, want, cant, dissapoint
Topic 6 Top Words:
        Highest Prob: treat, respect, way, understand, wish, consider,
        patient
        FREX: respect, digniti, treat, utmost, courtesi, consider, patienc
Topic 7 Top Words:
        Highest Prob: alway, help, staff, friend, recommend, found, best
        FREX: friend, alway, polit, recommend, help, hesit, accommod
Topic 8 Top Words:
        Highest Prob: amp, quot, hasn, sorri, word, bye, yeah
        FREX: quot, hasn, yeah, bye, phrase, putneymead, amp
Topic 9 Top Words:
        Highest Prob: surgeri, use, new, far, local, park, road
        FREX: park, road, street, femal, male, build, space
Topic 10 Top Words:
        Highest Prob: staff, recept, deal, peopl, member, job, train
        FREX: deal, train, recept, wit, member, abus, public
Topic 11 Top Words:
        Highest Prob: servic, difficult, improv, general, access, negat,
        etc
        FREX: improv, group, access, facil, environ, circumst, view
Topic 12 Top Words:
        Highest Prob: seen, time, lot, also, littl, children, especi
        FREX: drs, especi, whenev, children, seen, lot, littl
Topic 13 Top Words:
        Highest Prob: nurs, also, offer, attend, clinic, rate, organis
        FREX: clinic, rate, jab, flu, star, attend, nurs
Topic 14 Top Words:
        Highest Prob: rude, absolut, let, unhelp, bad, one, extrem
        FREX: rude, unhelp, abrupt, unprofession, arrog, unfriend,
        behaviour
Topic 15 Top Words:
        Highest Prob: phone, tri, answer, line, busi, someon, final
        FREX: answer, phone, hold, engag, messag, line, tri
Topic 16 Top Words:
        Highest Prob: feel, great, make, particular, love, person, welcom
        FREX: smile, eas, comfort, love, great, cheer, refresh
Topic 17 Top Words:
        Highest Prob: wait, time, hour, minut, late, long, run
        FREX: late, hour, wait, half, minut, min, queue
Topic 18 Top Words:
        Highest Prob: pain, symptom, suffer, wife, examin, chest, oper
        FREX: dress, chest, wound, shoulder, christma, ambul, lung
Topic 19 Top Words:
        Highest Prob: think, thing, review, sometim, quit, read, other
        FREX: bit, thing, rememb, goe, honest, other, quit
Topic 20 Top Words:
        Highest Prob: saw, right, diagnos, thought, differ, diagnosi, life
        FREX: heart, investig, diseas, diagnosi, diagnos, faith, histori
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Topic 21 Top Words:
Highest Prob: regist, complet, form, yet, sign, anoth, partner
FREX: form, fill, registr, certif, proof, charg, document
Topic 22 Top Words:
Highest Prob: medic, health, centr, opinion, extra, mile, assist
FREX: extra, mile, grove, riversid, cleric, reliabl, various
Topic 23 Top Words:
Highest Prob: test, hospit, blood, result, refer, referr, specialist
FREX: test, blood, result, scan, abnorm, referr, ultrasound
Topic 24 Top Words:
Highest Prob: inform, contact, complaint, respons, despit, date, record
FREX: contact, complaint, inform, record, despit, formal, state
Topic 25 Top Words:
Highest Prob: care, excel, receiv, provid, high, profession, famili
FREX: outstand, class, qualiti, excel, superb, care, exemplari
Topic 26 Top Words:
Highest Prob: issu, condit, occas, serious, sever, discuss, long
FREX: issu, term, ongo, resolv, chronic, condit, regular
Topic 27 Top Words:
Highest Prob: visit, home, recent, husband, mother, life, save
FREX: mother, husband, mum, father, dad, carer, district
Topic 28 Top Words:
Highest Prob: prescript, repeat, request, order, pharmaci, collect, medic
FREX: prescript, repeat, collect, chemist, pharmaci, order, readi
Topic 29 Top Words:
Highest Prob: treatment, concern, consult, advic, quick, follow, recent
FREX: prompt, dealt, appropri, treatment, necessari, outcom, concern
Topic 30 Top Words:
Highest Prob: appoint, book, work, day, avail, system, open
FREX: advanc, book, ahead, slot, avail, work, onlin
Topic 31 Top Words:
Highest Prob: told, ring, next, day, rang, today, got
FREX: appt, ring, tomorrow, next, till, pre, releas
Topic 32 Top Words:
Highest Prob: hope, must, continu, believ, situat, total, due
FREX: stress, air, staf, session, fresh, becom, gain
Topic 33 Top Words:
Highest Prob: said, went, told, refus, still, back, anoth
FREX: knee, depress, painkil, sleep, refus, said, went
Topic 34 Top Words:
Highest Prob: receptionist, ask, speak, tell, person, name, decid
FREX: speak, spoke, app, ask, receptionist, lie, ladi
Topic 35 Top Words:
Highest Prob: sure, someth, less, take, obvious, idea, import
FREX: pretti, otherwis, imagin, assum, push, someth, break
Topic 36 Top Words:
Highest Prob: walk, room, hear, door, whilst, sit, comput
FREX: room, door, chair, toilet, floor, window, enter
Topic 37 Top Words:
Highest Prob: will, look, ill, might, stop, doc, forget
FREX: doc, forget, earth, ill, stick, manor, might
Topic 38 Top Words:
Highest Prob: call, back, morn, day, later, afternoon, monday
FREX: afternoon, monday, friday, call, morn, thursday, tuesday
Topic 39 Top Words:
Highest Prob: poor, lack, left, manner, show, communic, skill
FREX: lack, empathi, mental, toward, learn, dismiss, disinterest
Topic 40 Top Words:
Highest Prob: patient, manag, nhs, number, rather, comment, meet
FREX: perhap, govern, meet, client, manag, stretch, target
Topic 41 Top Words:
Highest Prob: first, given, time, within, possibl, reason, expect
FREX: canâ, possibl, frame, within, prepar, specif, didnâ
Topic 42 Top Words:

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          Highest Prob: experi, impress, knowledg, approach, posit,
          confid, includ
          FREX: impress, compet, aspect, posit, humour, valu, encourag
Topic 43 Top Words:
          Highest Prob: need, find, abl, surgeri, although, rare, choic
          FREX: locum, find, occass, rare, unfair, choic, perman
Topic 44 Top Words:
          Highest Prob: good, realli, listen, happi, nice, rush, overal
          FREX: nice, good, clean, helpful, tidi, atmospher, rush
Topic 45 Top Words:
          Highest Prob: can, see, usual, hard, get, unless, mean
          FREX: can, usual, unless, hard, nigh, thay, hurley
Topic 46 Top Words:
          Highest Prob: thank, support, kind, team, fantast, wonder, everyon
          FREX: thank, support, prais, grate, team, empathet, kind
Topic 47 Top Words:
          Highest Prob: practic, gps, regist, recent, decis, experienc,
          consid
          FREX: gps, practic, readili, pro, provis, senior, decis
Topic 48 Top Words:
          Highest Prob: month, everi, end, sick, disappoint, fine, still
          FREX: sick, month, asap, six, everytim, end, shambl
Topic 49 Top Words:
          Highest Prob: telephon, system, howev, unabl, process, current,
          frustrat
          FREX: telephon, triag, altern, websit, design, obtain, advertis
Topic 50 Top Words:
          Highest Prob: made, explain, done, felt, time, take, put
          FREX: everyth, explain, nervous, fuss, made, felt, instant
Topic 51 Top Words:
          Highest Prob: appoint, week, day, see, emerg, two, make
          FREX: emerg, week, cancel, urgent, earliest, three, appoint
Topic 52 Top Words:
          Highest Prob: peopl, often, enough, may, lucki, fault, mayb
          FREX: often, mayb, cope, hit, suit, load, easier
Topic 53 Top Words:
          Highest Prob: surgeri, mani, pleas, practis, time, perfect, unlik
          FREX: practis, mani, east, north, perfect, town, wise
Topic 54 Top Words:
          Highest Prob: amp, apo, didn, couldn, wasn, doesn, wouldn
          FREX: apo, couldn, wouldn, isn, haven, amp, doesn
Topic 55 Top Words:
          Highest Prob: year, now, chang, last, sinc, ago, past
          FREX: sinc, chang, join, retir, yrs, downhil, last
Topic 56 Top Words:
          Highest Prob: seem, ever, place, actual, one, worst, interest
          FREX: worst, seem, liter, place, uninterest, whatsoev, rudest
Topic 57 Top Words:
          Highest Prob: don, like, bother, wrong, won, tell, annoy
          FREX: won, bother, don, stupid, idiot, dare, robot
Topic 58 Top Words:
          Highest Prob: doctor, problem, one, see, sort, surgeri, time
          FREX: doctor, problem, hill, anybodi, stuff, sort, reciev
Topic 59 Top Words:
          Highest Prob: move, area, regist, live, leav, differ, hous
          FREX: london, area, catchment, move, hous, villag, live
Topic 60 Top Words:
          Highest Prob: prescrib, infect, antibiot, didn, eye, ear, even
          FREX: ear, cream, tonsil, allergi, throat, midwif, allerg
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LDA topic model with 70 topics

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 Topic 1 Top Words:
          Highest Prob: hospit, went, told, month, week, letter, still
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FREX: ray, knee, inject, mri, letter, scan, accid
Topic 2 Top Words:
Highest Prob: just, ill, know, someth, sick, might, wors
FREX: rough, sick, funni, imagin, forbid, god, nonsens
Topic 3 Top Words:
Highest Prob: chang, better, bad, hope, now, think, must
FREX: practis, better, street, rest, bunch, titl, load
Topic 4 Top Words:
Highest Prob: even, tell, els, anyth, bother, sorri, just
FREX: somewher, els, lie, clue, okay, dare, mom
Topic 5 Top Words:
Highest Prob: two, last, occas, sever, surgeri, past, three
FREX: occas, numer, manor, separ, squeez, disappoint, perman
Topic 6 Top Words:
Highest Prob: alway, help, happi, polit, surgeri, found, busi
FREX: alway, happi, polit, accommod, pleasant, overal, satisfi
Topic 7 Top Words:
Highest Prob: nurs, practition, need, also, surgeri, doctor, time
FREX: practition, dress, wound, nurs, backward, praction, tea
Topic 8 Top Words:
Highest Prob: friend, recommend, profession, surgeri, welcom, knowledg, excel
FREX: clean, welcom, friend, recommend, hesit, courteous, atmospher
Topic 9 Top Words:
Highest Prob: say, realli, like, thing, nice, honest, just
FREX: realli, honest, say, stuff, thing, gold, worth
Topic 10 Top Words:
Highest Prob: get, appoint, tri, ring, line, phone, imposs
FREX: imposs, engag, line, tri, ring, get, queue
Topic 11 Top Words:
Highest Prob: appoint, need, emerg, difficult, abl, urgent, usual
FREX: difficult, urgent, usual, emerg, often, abl, ideal
Topic 12 Top Words:
Highest Prob: person, one, although, other, certain, way, quit
FREX: fair, certain, world, other, although, doubt, million
Topic 13 Top Words:
Highest Prob: appoint, book, system, avail, telephon, onlin, work
FREX: system, onlin, book, advanc, avail, triag, telephon
Topic 14 Top Words:
Highest Prob: wait, hour, minut, time, appoint, late, long
FREX: wait, hour, late, minut, sit, min, schedul
Topic 15 Top Words:
Highest Prob: visit, home, husband, surgeri, mother, mum, elder
FREX: father, mother, husband, dad, mum, carer, elder
Topic 16 Top Words:
Highest Prob: help, thank, best, kind, much, love, great
FREX: extra, love, brilliant, kind, amaz, fantast, troubl
Topic 17 Top Words:
Highest Prob: call, phone, back, answer, told, speak, today
FREX: call, answer, messag, phone, tomorrow, back, hung
Topic 18 Top Words:
Highest Prob: staff, recept, help, surgeri, member, also, admin
FREX: helpful, recept, staff, admin, member, recomend, proffesion
Topic 19 Top Words:
Highest Prob: problem, health, issu, doctor, trust, mental, listen
FREX: mental, health, solv, student, issu, physic, trust
Topic 20 Top Words:
Highest Prob: actual, either, cost, age, avoid, end, worst
FREX: luck, redial, somebodi, switch, caller, connect, actual
Topic 21 Top Words:
Highest Prob: lot, sometim, think, littl, especi, understand, bit
FREX: drs, bit, lot, donâ, itâ, lodg, sometim
Topic 22 Top Words:
Highest Prob: feel, made, felt, explain, make, experi, interest
FREX: felt, feel, made, interest, judg, light, slight
Topic 23 Top Words:
Highest Prob: come, talk, place, room, hear, door, across
FREX: across, hear, stand, dirti, privaci, miser, confidenti
Topic 24 Top Words:
Highest Prob: amp, quot, said, repli, told, ask, inhal

FREX: quot, certif, hello, inhal, bye, repli, said
Topic 25 Top Words:
Highest Prob: apo, didn, amp, couldn, wasn, wouldn, hadn
FREX: wasn, didn, hadn, couldn, shouldn, hasn, weren
Topic 26 Top Words:
Highest Prob: clinic, use, improv, access, etc, park, main
FREX: park, build, car, site, locat, modern, facil
Topic 27 Top Words:
Highest Prob: manag, contact, complaint, respons, note, record, clear
FREX: record, complaint, updat, respons, contact, formal, address
Topic 28 Top Words:
Highest Prob: prescript, repeat, request, medic, order, pharmaci, collect
FREX: repeat, prescript, chemist, order, collect, pharmaci, jab
Topic 29 Top Words:
Highest Prob: good, work, keep, patient, job, hard, pleas
FREX: aspect, keep, clinician, oblig, role, good, exceed
Topic 30 Top Words:
Highest Prob: concern, advic, given, treatment, follow, confid, reassur
FREX: appropri, reassur, confid, concern, prompt, understood, swift
Topic 31 Top Words:
Highest Prob: life, regular, wife, pressur, check, save, diabet
FREX: heart, diabet, weight, attack, wife, healthi, control
Topic 32 Top Words:
Highest Prob: patient, deal, peopl, attitud, face, speak, lack
FREX: face, toward, custom, train, abus, skill, languag
Topic 33 Top Words:
Highest Prob: peopl, obvious, probabl, mayb, frustrat, realis, seem
FREX: femal, male, merg, realiti, probabl, curt, dog
Topic 34 Top Words:
Highest Prob: care, receiv, support, medic, excel, centr, level
FREX: support, dedic, shown, qualiti, strength, superb, guidanc
Topic 35 Top Words:
Highest Prob: day, told, morn, appoint, next, week, rang
FREX: morn, monday, next, friday, afternoon, tuesday, wednesday
Topic 36 Top Words:
Highest Prob: symptom, suffer, left, serious, caus, stress, refus
FREX: depress, anxieti, dismiss, threaten, worsen, disord, distress
Topic 37 Top Words:
Highest Prob: seem, gone, rare, miss, locum, twice, list
FREX: hill, downhil, hit, locum, play, music, cope
Topic 38 Top Words:
Highest Prob: doctor, see, give, need, advis, surgeri, now
FREX: kid, see, appoit, advis, give, nearest, tire
Topic 39 Top Words:
Highest Prob: ask, inform, question, name, form, detail, sign
FREX: form, fill, comput, registr, sign, name, detail
Topic 40 Top Words:
Highest Prob: like, wrong, know, wast, everi, less, proper
FREX: singl, awkward, silli, dread, idiot, stupid, liter
Topic 41 Top Words:
Highest Prob: nhs, privat, pay, basic, free, money, paid
FREX: tax, pay, charg, money, paid, tick, privat
Topic 42 Top Words:
Highest Prob: surgeri, now, struggl, idea, one, even, get
FREX: doc, rid, anymor, horrend, branch, struggl, reach
Topic 43 Top Words:
Highest Prob: pain, son, gave, infect, took, antibiot, examin
FREX: chest, cough, throat, leg, sleep, temperatur, swollen
Topic 44 Top Words:
Highest Prob: will, surgeri, possibl, sort, receptionist, make, soon
FREX: center, air, fresh, alot, unhappi, soon, will
Topic 45 Top Words:
Highest Prob: week, walk, final, someon, told, centr, hold
FREX: cancel, hold, final, unaccept, spent, minimum, shambl
Topic 46 Top Words:
Highest Prob: treat, practic, patient, respect, approach, consider, digniti
FREX: respect, courtesi, utmost, digniti, valu, humour, proactiv
Topic 47 Top Words:
Highest Prob: patient, poor, general, practic, unfortun, experi, communic

FREX: communic, adequ, essenti, user, declin, stretch, general
Topic 48 Top Words:
Highest Prob: servic, provid, inform, comment, posit, involv, negat
FREX: decis, feedback, involv, particip, comment, anonym, posit
Topic 49 Top Words:
Highest Prob: year, famili, mani, found, practic, surgeri, doctor
FREX: whenev, accomod, class, compar, retir, famili, alik
Topic 50 Top Words:
Highest Prob: doctor, seen, surgeri, differ, everyth, time, straight
FREX: london, ball, king, everyth, univers, smoke, birmingham
Topic 51 Top Words:
Highest Prob: time, take, work, around, full, mean, surgeri
FREX: drive, worker, spend, full, bus, plus, journey
Topic 52 Top Words:
Highest Prob: one, can, need, find, pretti, coupl, fob
FREX: pretti, con, fob, pros, tricki, scienc, one
Topic 53 Top Words:
Highest Prob: practic, regist, move, sinc, new, area, surgeri
FREX: move, catchment, reloc, north, join, bridg, area
Topic 54 Top Words:
Highest Prob: high, profession, team, thank, enough, excel, prais
FREX: prais, credit, team, sincer, compassion, compliment, truli
Topic 55 Top Words:
Highest Prob: test, blood, result, done, send, taken, sampl
FREX: test, result, blood, sampl, abnorm, needl, pregnanc
Topic 56 Top Words:
Highest Prob: babi, check, turn, young, pregnant, school, got
FREX: babi, birth, immunis, school, rung, boy, feed
Topic 57 Top Words:
Highest Prob: despit, unabl, yet, process, surgeri, accept, fail
FREX: fail, travel, polici, four, promis, common, accept
Topic 58 Top Words:
Highest Prob: medic, treatment, consult, condit, requir, immedi, refer
FREX: consult, necessari, activ, condit, ailment, investig, oper
Topic 59 Top Words:
Highest Prob: appoint, week, absolut, left, get, ridicul, joke
FREX: joke, ridicul, everyday, appoin, absolut, lotteri, pointless
Topic 60 Top Words:
Highest Prob: patient, number, practic, local, consid, nhs, may
FREX: resourc, increas, govern, larg, serv, benefit, difficulti
Topic 61 Top Words:
Highest Prob: never, can, want, ever, get, time, choos
FREX: never, forget, choos, forev, apart, closer, can
Topic 62 Top Words:
Highest Prob: review, patient, rather, howev, opinion, simpli, appear
FREX: review, subject, interact, compel, lead, educ, key
Topic 63 Top Words:
Highest Prob: second, first, partner, mention, month, anoth, situat
FREX: partner, cross, third, seven, trip, stitch, failur
Topic 64 Top Words:
Highest Prob: gps, particular, far, surgeri, everi, noth, time
FREX: gps, far, perfect, prefer, hurri, effort, avenu
Topic 65 Top Words:
Highest Prob: receptionist, rude, unhelp, front, extrem, let, ignor
FREX: unhelp, rude, unprofession, arrog, abrupt, condescend, uncar
Topic 66 Top Words:
Highest Prob: appt, get, dont, cant, need, want, ive
FREX: appt, ive, dont, cant, app, doesnt, apt
Topic 67 Top Words:
Highest Prob: look, old, daughter, away, children, worri, child
FREX: daughter, child, toddler, unwel, law, worri, children
Topic 68 Top Words:
Highest Prob: well, surgeri, recent, effici, quick, extrem, impress
FREX: quick, impress, easi, definit, dealt, effici, dispensari
Topic 69 Top Words:
Highest Prob: amp, apo, don, doesn, isn, haven, can
FREX: don, doesn, apo, amp, won, isn, aren
Topic 70 Top Words:
Highest Prob: prescrib, take, stop, medicin, medic, ear, side

FREX: ear, medicin, drug, remov, nose, syring, danger

Appendix 2: Topic labels

The labels are for the LDA topic model that generated 60 topics from the GP reviews corpus. Each topic label is accompanied by a sample review which is representative of the topic

Topic 1	**Topic 2**	**Topic 3**
Grateful child treated	**Helpful practice**	**Not worth the tax paid**
"My daughter has an ear infection. Rang Giffords and someone rang me back quickly. We were going on holiday that day and this person was so helpful, got me in straight away and helped us out. Very grateful."	"Nothing is too much trouble and all the staff listen to what is bring said and try there best to help at all times Much better than big practices ticking boxes"	"After paying all the national insurance and tax there should be a fairly-good local doctors but after trying to get an appointment and finally seeing a doctor I was told to pay for private health care by the doctor and recieptionist. Absolute waist of time"
Topic 4	**Topic 5**	**Topic 6**
Appointment impossible	**[meaning not certain]**	**Respectful and understanding**
"It is an absolute nightmare to get an appointment at this surgery. Even if you ring at 8am you can never get through"	"Best doctors espically one doctor in particular they always know what is exactly wrong and knows whats wrong the receptionists dont really like ask u whats problem then tell u dont think u willl get an appoitment because its a cold when they have no right to say that some receptionist is rude but all drs and nurses r great"	"have always been treated with the utmost respect and doctors have gone out of their way to help me."
Topic 7	**Topic 8**	**Topic 9**
Friendly doctors	**[citing what GP staff say]**	**Parking access problem**
"Friendly staff who are happy to help and the doctors are always offering me advice. I would recommend this GP surgery to all my friends and family."	"Always geting an apoitment, without saying "urgent". Always geting propa treatment,and friendly stuff."	"Having undergone extensive knee surgery I can drive but cant walk distance. Not disabled so cant use disabled parking. No on street parking. Nelson st car park full of police cars. Have to use tudor sq car park . Not happy"
Topic 10	**Topic 11**	**Topic 12**
Receptionists need training	**Difficult access**	**Parents used it much for kids**
"Appalling: both reception staff and medical staff. This practice must be a lesson in how	"This surgery has difficulty in providing access to services for working people and a general manager with a poor attitute in response to resolving complaints. Consistent access to individual GPs	"I have been attending this surgery since 1986, i have seen Drs arrive and leave, some have been very good, some not so. Some times there are hold ups, and not seen on time ,but most Drs

NOT to deal with the public."	difficult as a number of the practice work part time hours."	have this problem at some time or other. Some Drs are more friendly then others.As is the staff on the desk Over all i like this Drs. and have told my friends that this is how i feel."
Topic 13	**Topic 14**	**Topic 15**
Star nurse service	**Arrogant and unprofessional**	**Can't reach on phone**
"My above star rating review is of the surgery overall. Regarding the flu jab service I would rate it as 5 star, excellent service every year. Thank you."	"Incredibly bad from the outset with a very rude and unprofessional doctor. Rarely have I met anyone quite so arrogant!"	"I am currently still on hold to try and get an appointment and have been for 30 minutes, they have clearly answered the phone and then put me on hold.... shocking!"
Topic 16	**Topic 17**	**Topic 18**
Comforting	**Long wait**	**Suffering**
"Thank you so much for your kindness. Your bedside manner is professional and it was a pleasure to meet you. Keep that lovely smile always."	"once again 50 min delay in seeing doc no apology explanation or warning that the doctor was running late and the music in the waiting room gets so annoying after the first half hour"	"I was told that I had Planter Fasciitis in my heel and a trapped nerve causing the pain in my back and arm. I was given treatment for both of these issues and am now free from pain in both."
Topic 19	**Topic 20**	**Topic 21**
Some good some bad	**Right heart diagnosis**	**Difficult registration**
"Been reading these reviews, i have no trouble getting to see a doctor everyone is so lovely helpful so cut them some slack will you, they work hard under a lot of pressure, lots of patients are happy would be nice to see good reviews on here for change We'll done everyone at walderslade village surgery your all great in my eyes ignore all the bad reviews	"I would like to thank the Doctor for acting promptly. The doctor suspected heart attack and was correct they saved my life for which I am erternally grateful and thank you to the rest of the team at the practice for there support and help since my heart attack"	"Unfortunately you cannot register with them if you work 9-5 as they only accept registrations during 10-12 and 2-4 weekdays. Partners are not allowed to hand in your completed form. Unhelpful."

they are not worth reading"		
Topic 22	**Topic 23**	**Topic 24**
Go extra mile	**Difficult referrals**	**Contact information missing**
"Having attended Litchdon Medical Centre for 7 years plus I have nothing but the highest opinion of their staff and medical services. Friendly, courteous, highly professional care at all times. You are in the safest hands if you are a patient at Litchdons."	"Problems have arisen with referrals for treatment to Hiilingdon Hospital as the surgery is in Ealing NHS area and I live in Hillingdon NHS area. This has happened for blood tests and recently for Diabetic Retinal check ups where I have sent sent to Ealing Hospital who do not have my notes.."	"The email points of contact are hard to find, however when they are found, they are invalid email addresses e.g. the practice manager's email address was given but was promptly returned as invalid email address"
Topic 25	**Topic 26**	**Topic 27**
Excellent care quality	**Poor chronic condition treatment**	**Arranged care at home**
"1st class practice providing exceptional care to my friends and family. I would rate highly all aspects of care. Highly professional and motivated doctors, nurses and staff."	"Unfortunately the service provided at this surgery has been incredibly poor. I rely on medication for my epilepsy, and on several occasions there have been drastic let downs in communication and issues which have interfered with my access to (my crucial) meds. I would recommend against joining unless you have no medical issues and are not reliant on your surgery"	"The doctors have been very good to me and my wife. When she was ill with cancer we got home visits and they arranged to have medications delivered to the house, they arranged district district nurses, hospice at home, and a hospital bed. Could not have been more helpful"
Topic 28	**Topic 29**	**Topic 30**
Prescription not realised	**Prompt treatment**	**Advanced booking unavailable**
"I have a monthly prescription which is requested by my local chemist . On Tuesday a request was sent through to the surgery and once again no Prescription has arrived at the chemist. . Very disappointed"	"Prompt action by G.P. Clear explanation and advice provided, happy with the treatment received."	"They have scraped 14 day appointments. You can only book 48 hour in adavnce making it very difficult to arrange routine appointments around work commitments."
Topic 31	**Topic 32**	**Topic 33**
Hard to book on phone	**Big changes in GP service**	**Distressing treatment for condition**

"This surgery has a ridiculous system for booking appts. You call at 2PM for an appt 2 days later but when I finally got through at 2.20PM, the appts had all gone and you then have to wait until 2PM the next day to repeat the cycle. On that basis, how would you ever get one?"	"After 30 years of sometimes good care. I now know I must leave. I have become increasingly alarmed at the lack of care over the months. I have finally reached the stage where I feel that after decades of contact, I can no longer trust the practice. I have a serious condition and it must be about 18 months since I could actually see my doctor. The voice at the end of the phone would not visit and insisted on diagnosis from my homebound laymans description. Not my idea of care for older people in the twenty-first century."	"Everything was fine , but the scales for my weight were 1 stone out . I thought my scales were wrong and i had lost a stone ! Went out to buy some new digital scales and realised no , your scales are wrong !!"
Topic 34	**Topic 35**	**Topic 36**
Situation with receptionists	**Unhelpful**	**Insufficient facilities**
"3 receptionists gave me 3 different instructions regarding to the appointment. Finally, I was told on phone that my prescription is ready to collect. When I came, another receptionist told me that there's no prescription on my name and asked me about the name of another receptionist who said the prescription is ready to collect! You have to ask the name of the receptionists whenever to call the GP!"	"good points Can more or less always get a same day appointment bad points They offer very little at the surgery. They don't take bloods- they send you to Dulwich hospital or King's for pretty much everything which means not only do you need to take time out for the initial GP appointment you then have to go to the hospital and wait in a queue to get bloods taken. Same goes for smear tests etc. Not entirely sure what they actually do save writing prescriptions. Really poor service."	"*had to wait 2 hrs at the sit and wait clnic with a child, there were 32 people in front of us\n*system to call patients needs urgent attention, people could not hear their names and were missing there slots, there need to be a screen\n*no water machine\n*no toilet roll or sanitary bags in the toilet\n*childrens toys are poor quality/quanity"
Topic 37	**Topic 38**	**Topic 39**
[meaning not certain]	**Hard to reach on phone**	**Poor manners**
"Since I have become ill, I have found that the staff have always been polite and	"I called this morning. Was told the doctor would call me back. 4 hours later no call back. I called back and was on hold for half an hour then someone answered and hung up. Called back straight away,	"Practice manger has no authority GPs lack compassion poor communication rud and dismissive manner towards patients"

understanding to me despite my mood swings at the beginning of my illness, yep I was young and in denial but they have always had my well being in their thoughts and they have always done their best to look after me. With their help, I have now accepted my illness and I only hope that we can move on together. They are a great team."	again on hold for another half another. Ridiculous."	
Topic 40	**Topic 41**	**Topic 42**
patient engagement	**Advising others**	**Competent and impressive**
"This practice has a very active Patient Panel which meets monthly, mostly with the Management, discussing even the most challenging issues within the practice. When the Panel offers helpful information and advice, this is acted upon and the Management subsequently reports back. Every Patient Panel member comment is taken seriously and responded to, as is every complaint from any patient. There is an excellent family feel to the practice which includes all staff. I think the Patient Panel, in particular,	"Getting an appointment is bun fight at 0800, that has moved to 0730. You'll queue for ages, then maybe get one of the appointments that are available, if not repeat for tomorrrow. Call later in the day, and expect a wait time for your call to be answered of over an hour. Yes, over an hour, listening to . Thank you for holding, your call will be answered shortly. Thank you for holding, your call will be answered shortly. Thank you for holding, your call will be answered shortly. Thank you for holding, your call will be answered shortly. Thank you...	"In my experience Reception team always professional, helpful and good humoured. Doctors approachable and obliging. Compared to other London medical experiences, including hospital, I'd definitely take Sternhall."

should be used as a model for other Patient Panels in the city."		
Topic 43	**Topic 44**	**Topic 45**
Surprising service	**Nice and clean**	**Usually difficult appointments**
"I had to visit the walk in center at broughton gate a few times as I have not been able to get an appointment at my own GP surgery. I found the service there to be excellent. the receptionist and doctors have always been most helpful.i would defintly be telling my friends and family about broughton gate."	"Clean bright surgery. Friendly receptionists. Good appointment availability. Efficient doctors. Very good surgery, very good doctors and very good services (physio and midwife inhouse.) I have always had a good experience at this surgery and am happy with the care my daughter and I have received."	"so many patients means that it takes hours to get an answer on the phone.It means that there is usually a wait of 2 weeks to see a doctor.or a week or more to see a nurse unless it is an emergency. Staff in reception try very hard and are as helpful as they can be"
Topic 46	**Topic 47**	**Topic 48**
Saying thanks	**Impressive practice**	**Bad experience**
"My doctor and their team have been incredibly supportive during the last year to me and my family, they have truly been compassionate and caring and extremely helpful."	"I have been with this practice for a couple of years. Their GPs are professional and respectful. My GP is experienced, friendly and polite. I strongly recommend this practice and I hope that my new practice was as good as this one."	"I have a four month old Son who has a facial skin infection, his medication is due to end in the next few days and we were told to arrange an appointment for the day after as they would need to see if it is working or getting worse, Could I get an appointment???? could I heck. I rang dead on the 8.30 and 12.30 times and was number one in cue both times only to be told nothing was avaliable despite pleading with them that this was a baby!!!!!. Apparently a four month old baby with a facial skin skin infection is not compulsory and will likely just have to wait three weeks or more I expect need I say more"
Topic 49	**Topic 50**	**Topic 51**
Ineffective booking system	**Sharing feelings**	**Emergencies without appointment**
"The medical records displayed on the Pateinet Access website are inaccurate. When I asked for them to be	"Everything is explained to me regarding my treatment. The staff take the time to let me ask questions. I felt that I was treated as an individual. Would recommend."	"Never get appointment when needed nothing can be prebooked for at least two weeks . For same day appointment phone is two busy between 8.00 - 8.30 by the time anyone answers the

corrected, the manager explained that that this was not possible. In implementing the new system they had simply reloaded old/inaccurate reords from the old system. Surely a key part of any IT implementation is to check/correct data beofre loading it onto the new system !!"		call all appointments have gone"
Topic 52	**Topic 53**	**Topic 54**
Healthcare system not good	**Pleasant experience**	**Unhappy with a quotation**
"Clever way of keeping hospital waiting times down!! Shocking how badly run this is... I came in with foot injury after waiting 4hours I was then transferred to a&e! Not enough seats not enough staff, really bad... Leicester royal can not cope with amount of people using it, become about stats rather then people!!"	"I have been a patient of the surgery for very many years and I have always been very pleased with the surgery the doctors and staff. They are all very helpful and give sufficient time to prolems and I would recommend the surgery"	"The receptionists are so rude on the phone! They answer saying 'name.' 'birthday' '1.30?' 'bye.' Unbelievable only just moved to Durham and never seen anything like it."
Topic 55	**Topic 56**	**Topic 57**
Visible changes	**The worst ever**	**annoying**
"It had changed a good deal since the previous incumbent retired a couple of years ago (we were their patients for nearly 40 years). I now find that up-dates are coming	"worst ever GP I ever had, I request prescription more that 4 day ago and nothing in there , no prescription , no medication, no any information when will get it. Worst, worst worst"	"The receptionists are incredibly rude and speak to you like dirt. They don't even smile and say hello when you walk over."

into place and appear to be an improvement and are not intrusive. We are very happy with the way the surgery is run."		
Topic 58	**Topic 59**	**Topic 60**
One doctor is unique	**Comparing GP practices**	**Maybe misdiagnosis, ear**
"All the doctors are nice and helpful apart from one doctor. Never book an appointment with that doctor. The doctor never listens, is unkind. Whenever we went to see the doctor they were very unaccomodating and never listened to our problems."	"Have recently moved to the area and was reluctant about leaving my previous GP but this Practice has been so helpful in registering me and have sorted out my medication with no hassle at all. I would highly recommend this Practice to anyone moving into the area."	"Went in with one ear infected, came out with 2. Should we be disinfecting otoscopes between transmission to infected ear to none infected ear? I think we should. Thankyou."