Quality of Life Assessment of Diabetic patients from health-related blogs

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February 19, 2019

Abstract

Motivations: People are generating an enormous amount of social data to describe their health care experiences, and continuously search information about diseases, symptoms, diagnoses, doctors, treatment options and medicines. The increasing availability of these social traces presents an interesting opportunity to enhance timeliness and efficiency of care. By collecting, analyzing and exploiting this information, it is possible to modify or in any case significantly improve our knowledge on the manifestation of a pathology and obtain a more detailed and nuanced vision of patients’ experience, that we call the “social phenotype” of diseases.

Materials and methods: In this paper we present a data analytic framework to represent, extract and analyze the social phenotype of diseases. To show the effectiveness of our methodology we presents a detailed case study on diabetes. First, we create a high quality data sample of diabetic patients’ messages, extracted from popular medical

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forums during more than 10 years. Next, we use a topic extraction techniques based on latent analysis and word embeddings, to identify the main complications, the frequently reported symptoms and the common concerns of these patients.

Results: We show that a freely manifested perception of a disease can be noticeably different from what is inferred from questionnaires, surveys and other common methodologies used to measure the impact of a disease on the patients' quality of life. In our case study on diabetes, we found that issues reported to have a daily impact on diabetic patients are diet, glycemic control, drugs and clinical tests. These problems are not commonly considered in Quality of Life assessments, since they are not perceived by doctors as representing severe limitations.

Keywords: social phenotype, diabetic patients, social analytics, LDA, topic clustering, word embeddings, quality of life assessment.

1 Introduction

On-line patient health data is increasing exponentially. Every day, through social networks, search engines, online forums, web sites, mobile applications, IoT devices, etc., people generate an enormous amount of health information [5]. This digital data (often referred to as the "digital phenotype" [16]) includes symptoms, medical experiences, bio data, biometric information, web search queries, personal stories and medical records. They represent the footprints of the patients health status and foster large-scale and low-cost analysis of common diseases [8] for many applications, such as syndromic surveillance [21], adverse drug reactions [15], and "social phenotyping" of diseases, i.e., a subjective and unfiltered picture of perceptions, health conditions, feelings and lifestyles of people affected by a given disease. The social phenotype has a value that goes beyond the physical, laboratory and clinical imaging examinations, which represent the traditional approaches to define the phenotype of a disease. By collecting, analyzing and integrating this information in an appropriate manner, it is possible to obtain a more detailed and "nuanced" vision of patients, taking into account different expressions

\footnote{Note that our notion of social phenotype is more focused than that of digital phenotype. The latter includes a variety of digital data, the former is concerned only with social traces.}
of diseases; the experience lived outside the traditional syndromic care and monitoring structures; the symptoms that are perceived as more limiting; the greater or lesser tolerance to drugs. This information is also very useful to complement standard survey-based techniques to assess patients’ Quality of Life (QoL). Although QoL surveys are very useful in assessing patients’ evaluations of care delivery, administered questionnaires reflect the care-givers’ view of the factors that mostly influence the health status and everyday life, while the social phenotype fosters a patient-centric perspective.

Leaning on these concepts, in this paper we gathered an extensive amount of health-related textual data from four popular medical forums. In these web platforms, patients submit health problems, questions and personal experiences to doctors. We applied text analytics and topic detection on these data with the purpose of answering the following research questions:

1. R1: What are the main complications reported by patients for selected diseases? Which symptoms are more frequently reported by patients?
2. R2: Are there gender/age differences in a disease perception?
3. R3: Does this “patient-centric” study of a disease perception correspond to published results using traditional Quality of Life assessments?

The paper is organized as follows: In Section 2 we summarize related literature. In Section 3 we describe the process of data collection and filtering, and the adopted topic extraction algorithm. Section 4 is dedicated to the analysis of the social phenotype of a specific and highly diffused disease, diabetes. Finally, Section 5 presents a summary of findings and concluding remarks.

2 Related work

Recent years have seen increasing interest in patient-centered care and in the improving of the patient experience. At the same time, through the Internet, people are generating an enormous amount of data to describe their experiences of healthcare. In fact, more and more often patients use the Web 2.0 technologies to search for information about diseases, symptoms, diagnoses, doctors, treatment options and medicines. They also search for support from online communities and post states about their conditions and their
sensations [13]. The increasing availability of this information presents an interesting opportunity to enhance timeliness and efficiency of care. Greaves et al. [8] describe this growing body of information on the Internet as a cloud of patient experience.

Jain et al. [9] starting from Richard Dawkins’ idea of an extended phenotype (phenotypes should not be limited just to biological processes, but extended to include all effects that a gene has on its environment inside or outside of the body of the individual organism [9]) introduced the concept of "digital phenotype". Through technology, including social media, search engines, online communities, forums, blogs, wearable technologies and mobile devices, people are generating an enormous amount of health-related data that can provide deep knowledge of patients health. These sources of information give us the footprints of the patients health status and could enrich notion of extended phenotype in a substantial way. Precisely, when gathered and analyzed suitably, such data provide a more comprehensive and nuanced view of the experience of disease (from diagnosis to treatment) and expand our ability to identify and diagnose health conditions.

Leaning on these concepts, in the last years, several studies showed that it was possible through machine learning techniques to detect patterns in data gathered from forums or social networks related to patient experience, in order to make decisions or predictions. Furthermore, there is an ample literature (see [24] for a survey) that demonstrates the possibility to analyze different types of discussion forums or blogs for obtaining useful information. Recent work more related to the objectives of this paper is summarized in what follows.

Verberne et al. [22] investigate the feasibility of thread summarization in patients’ support forum, selecting the most relevant sentences from a thread while hiding the less relevant sentences. They collected two sets of reference summaries for 100 randomly selected threads, with at least 10 posts, from the Facebook group of a patient support community: expert summaries and crowdsourced summaries. For each discussion thread they calculated the agreement between each pair of raters in terms of Cohen’s k. They found that the inter-rater agreement in crowdsourced summaries is low, close to random (k=0.081); while the inter-rater agreement in expert summaries achieved a considerably higher, fair value (k=0.267). Afterward, they selected the number of votes for a sentence as dependent variable and features related to frequency, similarity and position of the words as independent variables. They trained two linear regression models using the two types of reference
summaries and the selected variables. The models looked to be similar. So they concluded that it is possible to train a summarization model on crowdsourced information that is similar to an expert model, even if the inter-rater agreement for the crowdsourced summaries is very low.

White et al. [23] examined the use of web search behaviors for detecting neurodegenerative disorders (ND), such as Parkinsons disease (PD) and Alzheimers disease (AD) from search activities. They used a total of 18 months (from September 2015 to February 2017) of anonymous logs of United States search activity from the Microsoft Bing web search engine, containing millions of English-speaking searchers (31,321,070). From the full set of logs, searchers who input queries containing first-person statements about PD diagnosis were used as evidence of receiving a PD diagnosis. Multiple additive regression trees (MART) classifiers were trained to detect evidence of PD diagnosis. 10-fold cross-validation was used to train and test the classifier. Classifier sensitivities for PD discovery were 94.2/83.1/42.0/34.6% at false positive rates (FPRs) of 20/10/1/0.1% respectively (AUROC=0.9357). Furthermore, the method in this study was scaled to Alzheimers disease. In this case, sensitivities for AD detection were 91.0/81.5/38.8/26.1% at false positive rates (FPRs) of 20/10/1/0.1% respectively (AUROC=0.9135). The results offered evidence that the existence of NDs in web searchers was detectable from streams of data through an analysis over time.

Mirheidari et al. [14] using conversation analysis (CA), showed that a machine learning approach to analyze transcripts of interactions between neurologists and patients, who described memory problems, can differentiate people with neurodegenerative memory disorders (ND) from people with functional memory disorders (FMD). Firstly, 15 patients with ND and 15 patients with FMD, whose diagnoses could be established with wide certainty by the doctors, were selected for the study. Later, an automatic speech recognition (ASR) system and a diarization tool produced the written records of conversations. The output of the ASR+Diarization was passed on to the CA-style feature extraction unit which selected features related to the time of a conversation’s turn, the pauses in speech and the words used. Afterward, the features extracted were used to train a set of five binary classifiers to differentiate between ND and FMD. Each classifier reached a significant level of accuracy (Perceptron: 97%; Linear SVM: 93%; AdaBoost: 93%; Linear via SGD: 93%; Random Forest: 90%).

Miller et al. [13] analyzed the content and characteristics of important health blogs to supply a more complete understanding of the health blogo-
sphere. They identified, through a purposive-snowball sampling approach, 951 health blogs during two periods: June to July 2007 and April to May 2008. All blogs were US focused, written in English and updated frequently. They selected as features for the analysis: main blog topics, demographic information, frequency of posts, presence or absence of links and comment section. Most blogs typically focused on bloggers experiences. Half of the blogs were written from a professional view, one-third from a patient perspective. The majority of the bloggers were female, aged in their 30s and highly educated. So, in conclusion, they proved that data gathered from health blogs could be aggregated for large-scale experimental investigations.

Kavakiotis et al. [11] starting from the fact that diabetes mellitus is rapidly emerging as one of the greatest international health challenges of the 21st century, conducted a systematic survey of applications of data analytic techniques on scientific papers regarding diabetes. They identified and reviewed data mining and machine learning approaches applied on diabetes research respect to these five themes: Prediction and Diagnosis through Biomarker Identification, Diabetic Complications, Drugs and Therapies, Genetic Background and Environment and Health Care and Management Systems. In general, 85% of those researches were conducted by supervised learning approaches and 15% by unsupervised techniques; Support Vector Machines (SVM) represented the most successful and widely used algorithm; clinical data-sets were principally used; the primary purpose of these studies was to extract valuable knowledge that led to new hypotheses aimed at a deeper understanding and further investigation into diabetes.

The literature review on patients’ blogs analytics shows that the majority of works concentrated on classification problems rather than deriving a comprehensive picture of patient’s perceptions and lifestyle. Although the idea of extracting the digital phenotype of diseases has been launched in [9], to the best of our knowledge, this is the first large-scale study in which the utility of this approach is demonstrated.

3 The Social Phenotype Extraction Process

This Section describes in more detail the processing steps to extract the Social Phenotype of a disease, shown in the workflow of Figure 1:

1. First, we collected a large number of threads from popular medical blogs in Italy from 2001 to 2018 (Section 3.1):
2. Secondly, we filtered from these blogs conversations related to diabetes (Section 3.2). Diabetes is one of the most common endocrine disorders, affecting hundreds of millions of people globally; furthermore, the number of diabetic people is estimated to grow dramatically in the upcoming years [5], also due to the increase in obesity and sedentarity.

3. Next, we applied a topic extraction technique based on latent analysis augmented with word embeddings (Section 3.3). Automatically extracted topics were found to nicely identify the main known complications of diabetes, complained symptoms, effects of drugs, and clinical tests, although no prior knowledge was provided to the topic learner. For a subset of messages, we have been able to infer personal data such as gender and age, using specific keywords (Section 3.4);

4. Finally, data analytics has been extensively carried on, to identify co-morbidities, symptoms, conditions and main patients’ concerns along different dimensions, such as type of complication, age and gender, thus deriving a synthetic representation of diabetic patients’ experience in their everyday life, which we call the social phenotype of a disease (Section 4).

3.1 Dataset creation

We scraped a large set of data (about 700 thousand threads containing more than 3 million messages) from the 4 most popular medical forums in Italy, medicitalia.it, forumsalute.it, paginemediche.it and pazienti.it. Conversations span from 2001 to June 2018, although the large majority of messages refers to the past 10 years. The total number of threads and messages is summarized in Table 1.

In this work, we decided to focus on a specific pathology: diabetes. We have chosen to examine the social phenotype of this widespread and problematic metabolic disease considering the following alarming statistics and evaluations:

- diabetes interests more than 415 million people worldwide;

Patients are anonymous and we have followed the current privacy regulations according also with the T.O.S. of the involved platforms.
Figure 1: Workflow of the Social Phenotype Extraction Process

| source            | number of threads | number of messages |
|-------------------|-------------------|--------------------|
| medicitalia.it    | 562 817           | 2 597 881          |
| forumsalute.it    | 38 404            | 431 480            |
| paginemediche.it  | 81 373            | 162 746            |
| pazienti.it       | 14 853            | 29 706             |
| Total             | 697 447           | 3 221 813          |
• 29.1 million of U.S. citizens had diabetes in 2012 (9.3% of the population);

• the proportion of the people with diagnosed diabetes is expected to increase (1 in 10 adults will have diabetes by 2040, and 1 in 3 adults of USA will have diabetes by 2050);

• diabetes care has been estimated at $1.31 trillion globally;

• diabetic patients have a 3-fold greater possibility of hospitalization in comparison to patients without this illness;

• for the same condition, people hospitalized with a diagnosis of diabetes stay in the hospital for more time than patients without a diagnosis of this disease;

• this pathology is the 7th cause of death in the USA in 2014 (24 deaths each 100,000 people);

• hyperglycemia is strongly connected with an increased risk of mortality and complications [9].

In Italy, the picture is very similar, if not worst: the prevalence of diabetes nearly doubled in thirty years. Compared to 2000, there are 1 million more people with diabetes and this is due both to the aging of the population and to other factors, including the anticipation of diagnoses (which brings to light previously unknown cases) and the increase in survival of patients with diabetes.

### 3.2 Classification of diabetic patients

Although most threads have category labels indicating the discussion topic, and although diabetes is one of the categories, after a closer inspection by a diabetologist (one of the co-authors) we concluded that the classification was often not accurate. First, some of the threads manually tagged as “diabetes” actually show a different symptomatology (although the patient fears to have diabetes symptoms), second, and more importantly, several diabetes-related threads are classified with other category labels, reflecting common diabetes complications and risk factors, such as cardiology, obesity, and others. For
this reason it has been necessary to re-classify all threads using automated, but eventually more performant, techniques.

To classify messages, we used the open-source library *FastText*. This software tool, developed by Facebook’s Artificial Intelligence Research (FAIR) lab, combines state-of-the-art Natural Language Processing and Machine Learning techniques [10]. The classification algorithm consists in a fast approximation of the *softmax classifier*, in which it is used a hierarchical structure (a tree, representing categories, assembled by using the Huffman algorithm) instead of a flat construction [10].

In this phase of our study, we devoted specific attention to the training and validation process, since we considered of particular importance to obtain a clean dataset of conversations clearly associated to diabetes, its complications and risk factors.

The *training set* was built as follows: we selected the threads that contained at least three times the prefixes ”diab” and ”insulin” (the roots of the most characterizing words of this specific disease) and we assigned to them the label ”DIABETES”. We adopted this approach, since it was manually verified on a sub-sample that, in this way, only the threads strongly connected to the pathology of interest were chosen. Next, we retrieved a dictionary of terms (key-words and key-phrases) related to diabetes from the site *diabetes.net*, we selected threads that did not contain any of these words homogeneously between categories, and we confer to these documents the label ”NO”. At the end of these operations, the resulting training set consisted of 380,000 threads, of which:

- 3,902 threads labeled as ”DIABETES”;
- 376,098 threads labeled as ”NO”.

Once the training set was built, we trained the model using various combinations of hyper-parameters. Subsequently, we selected the model that allowed us to achieve the best performance in the automatic evaluation tests. Finally, we used the best learned model to classify all the documents in the initial collection. *At the end, 10,388 threads, containing a total of 40,443 patients’ messages*[^3] *were classified as related to the pathology of interest.*

[^3]: Note that threads often include conversations between patients and doctors. Doctors’ messages, however, are clearly marked as such. For the purpose of this analysis, doctors’ messages have been deleted.
Table 2: Classification performances on the validation set

| metric               | score |
|----------------------|-------|
| Accuracy             | 0.993 |
| Error rate           | 0.007 |
| Precision            | 1     |
| Recall (TPR)         | 0.960 |
| Specificity (TNR)    | 1     |
| F-measure            | 0.980 |

To ensure data quality, we applied multiple validation techniques on this dataset. We first evaluated performances using the classic holdout method (70% training, 30% testing). With this method we detected no errors (zero False-Positives and zero False-Negatives). Next, we repeated automated evaluation using a validation set of discussion threads extracted from another specific forum exclusively dealing with diabetes (portalediabete.org) and we marked the 506 gathered threads with the label DIABETES. Subsequently, we extracted discussion threads from other forums related to medical areas not connected to diabetes on the site abcsalute.it, selecting only items that contained no terms strictly characterizing the disease. We assigned to the 2345 threads obtained in this way the label “NO”. Finally, with this validation set of 2851 instances, we tested the previously obtained classification model. The performances are shown in Table 2.

Lastly, we performed manual evaluation by experts. We sampled 500 threads from the original test set, with the predictions made by the model. 250 items in the sample presented the label ”DIABETES”, while the remaining 250 threads were labeled ”NO”. We then asked two diabetologists to manually evaluate the correctness of these predictions. We exercised three different degrees of judgment (Best case, Average case and Worst case) based on the severity of reporting False-Positives errors. For example, in the Average case we considered True-Positives all threads clearly connected to diabetes, or otherwise that presented in their messages the following elements: problems of glucose metabolism, metabolic study using a glycemic and insulinemic curve, metabolic syndrome, hyperglycemia, analysis of blood sugar and insulinemia, diabetes as a risk factor in the answer provided by the doctor, specific drugs to treat this disease.

For all three levels of judgment, the performances of the classification
Table 3: *Classification performance obtained from manual evaluation*

|                  | Average case | Worst case | Best case |
|------------------|--------------|------------|-----------|
| **Accuracy**     | 0.950        | 0.920      | 0.976     |
| **Error rate**   | 0.050        | 0.080      | 0.024     |
| **Precision**    | 0.900        | 0.840      | 0.952     |
| **Recall (TPR)** | 1            | 1          | 1         |
| **Specificity (TNR)** | 0.909    | 0.862      | 0.954     |
| **F-measure**    | 0.947        | 0.913      | 0.975     |

obtained from manual evaluation are listed in Table 3. In conclusion, according to the performed evaluations, it can be stated that the quality of the classification task resulted satisfactory and adequate for our context. The dataset of 40,443 patients’ messages was therefore finally adopted.

### 3.3 Topic detection

Our objective in this research is to characterize patients’ experience and focus on how they perceive the disease and its complications. To this end, topic extraction has been applied solely on patients’ messages in our collection (doctors’ messages have been excluded). In this context, a *topic* is a set of semantically and/or contextually related words or key-phrases, representing a coherent and frequent argument of discussion.

We adopted a hybrid approach to discover the main discussion topics of diabetic patients. First, we applied LDA [2] on the collection and then, we improved the quality of obtained clusters using the Word2Vec model.

Latent Dirichlet allocation (LDA) is a three-level hierarchical Bayesian model, in which each document is represented as a finite mixture, according to a Dirichlet distribution, over an underlying fixed set of topics. In turn, each topic is modeled by a probability distribution over words [2]. Word2Vec is a computationally efficient family of predictive models for learning word embeddings from large amounts of unstructured text data, introduced by Mikolov et al. [12]. Word2Vec consists in a multi-layer neural network. It takes as its input raw text and produces a continuous vector space, in which each single word in the corpus is mapped onto a corresponding vector of real numbers in a lower-dimension semantic space. Semantically similar vectors are located in close proximity to one another in the vector space. To compute both LDA and Word2Vec, we employed *Gensim*, an open-source
Python library for topic extraction and vector space modeling.

In the LDA phase, we calculated the term-document matrix from the collection of documents regarding diabetes, subsequently we processed and normalized this data structure, and finally we trained LDA with this matrix as input. To normalize the values in the matrix, we used as weight function the mean between TF-IDF and log-entropy models. The Log-Entropy model is a more sophisticated weighting scheme based on entropy. This model operates row-wise with no interaction between terms and produces normalized values in the range from zero to one. In this scheme, a reduced weight is assigned to a word that appears with equal probability between documents; while a more significant weight is given to a term whose occurrence is concentrated in few documents.

\[
local\_weight_{t,d} = \log (TF_{t,d} + 1)
\]

\[
global\_weight_{t} = 1 + \frac{\sum_{d} (\frac{TF_{t,d}}{\sum_{d} TF_{t,d}} \cdot \log (\frac{TF_{t,d}}{\sum_{d} TF_{t,d}}))}{\log (N + 1)}
\]

\[
final\_weight_{t,d} = local\_weight_{t,d} \cdot global\_weight_{t}
\]

At the end of this phase, we obtained 14 “temporary” topics, which where then refined in the subsequent phase.

During the Word2Vec phase, we trained the CBOW model of the Word2Vec family with the entire collection of discussion threads (concerning all types of diseases). We obtained a continuous vector space, able to model the contextual similarities and differences between words in the collection. We trained the Word2Vec model with the following parameters:

- \( min\_count = 100 \) (minimum frequency: the algorithm neglects all words with number of occurrences lower than the specified value);
- \( size = 100 \) (Dimensionality of the word vectors);
- \( iter = 100 \) (Number of iterations over the corpus).

\(^{4}\)the number of topics is an hyper-parameter of the LDA model. This number is commonly tuned experimentally in the LDA literature.
In the last phase, we improved the quality of the 14 topics previously obtained with LDA, using word embeddings learned during phase 2. For this purpose, we initially removed 30% of the least relevant words from each temporary cluster $T_i$ according to Word2Vec. Then, we added to each $T_i$ all the words that Word2Vec considered similar to those in $T_i$ with a similarity score higher than 0.6. At the end of these operations, we obtained 14 improved topics able to model quite accurately various aspects of the pathology under study.

![Intertopic Distance Map](image)

**Figure 2:** A visualization of topic 6, Hepathology

Figure 2 shows graphically the relevance of each topic and their intersections. In this view, the topics are plotted as circles in a two-dimensional plane. Topic centers are discovered by calculating the distance between topics, and then by using multidimensional scaling to project the inter-topic distances on the two dimensions. Moreover, each topic prevalence is encoded using the areas of the circles. These hyper-parameters have been experimentally tuned to obtain top quality topics, according to domain experts.
highlighted topic is topic 6, labeled *hepathology*). Saliency is based on the following probabilities:

- $\text{Pr}(w)$ represents the probability of randomly selecting the word $w$ from the collection (the frequency of the term $w$ normalized in the range between zero and one),

- $\text{Pr}(T \mid w)$ represents the likelihood that observed word $w$ was generated by latent topic $T$,

- $\text{Pr}(T)$ represents the likelihood that any randomly-selected word $w'$ was generated by topic $T$;

the saliency of a word $w$ is then defined by this equation [3]:

$$
\text{saliency}(w) = \text{Pr}(w) \cdot \sum_T \left( \text{Pr}(T \mid w) \cdot \log \left( \frac{\text{Pr}(T \mid w)}{\text{Pr}(T)} \right) \right)
$$

The 14 extracted topics are listed in Appendix 1 in descending order from the most frequent to the least predominant in the collection. For all topics, only the most significant terms are reported, in order of importance. All terms have been translated from Italian to English for readability. After a meticulous manual evaluation\(^{6}\) we assigned to each topic the label that seemed to be more appropriate and representative.

Appendix 1 shows that 9 clusters nicely\(^{7}\) correspond to the main known complications of diabetes (clusters 2, 4, 6, 7, 9, 10, 11, 12, 13 and 14); cluster 1 includes terms related to feelings and symptoms; cluster 3 is about dietary issues; cluster 5 is about clinical tests and drugs; cluster 8 includes terms related to diabetes in general (e.g. mellitus, insulin, glycemia, etc.) and finally, cluster 9 has no clear semantics\(^{8}\). As shown in Figure 2\(^{2}\) the largest cluster is cluster 1, labeled *symptoms-feelings*. This is the most important cluster, both because of its frequency, and because of the objectives of our analysis. For

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\(^{6}\)Note however that we did *not* manually adjusted the list of words in each topic: although there might be a few apparently spurious words, they still reflect similarity of usage, according to the adopted model.

\(^{7}\)Remember that topic clustering is an untrained methodology: no domain knowledge is available to the system.

\(^{8}\)"Everything else" clusters are an almost unavoidable phenomenon in clustering, although in our case it is a small cluster.
this reason, it has been further partitioned in 10 sub-clusters, using a semi-automated method summarized in Appendix 2, in order to group specific categories of symptoms, like polyuria, drowsiness and tiredness, eye problems etc. A further partition has been performed on the subtopic negative feelings, in order to distinguish between anger, sadness, stress and fear.

These topics and sub-topics are at the basis of the data analytic phase presented in Section 4.

3.4 Patients segmentation by gender and age

In all examined health blogs, patients are anonymous and have no IDs. Therefore, it is impossible even to understand if a patient has repeatedly participated in a discussion. However, for about a 25-30% of the threads, questions to doctors and discussions on symptoms and perceptions are reported by a patient’s relative or friend, rather than by the patient itself. This can be captured by key phrases, like ”my mother”, ”my husband”, and the like. This information is precious, since it allows, at least for a fragment of messages in our collection, to perform patients’ segmentation according to age and gender. For example, ”my mother” can with good confidence be attributed to an elder female diabetic patient.

First, to filter from the collection only messages authored by some relative of a diabetic patient, we selected discussion threads that mentioned a parental relation (e.g., ”my father”, ”my sister”, etc.) within the first fifty words. In fact, most of the time, we observed that when a user writes about his/her relative, the relationship is clarified in the first lines of a message or thread.

The evaluation of this classification process was conducted in a way similar to that described in Section 3.2, obtaining an accuracy of 0.93. Details are omitted for the sake of space.

For patient segmentation on this subset of data, we associated parental keywords in messages to two age groups, as follows:

- **old**: grandfather, grandmother, father, mother, uncle, aunt, father-in-law, mother-in-law;

- **adult/young**: husband, wife, boyfriend, girlfriend, brother, sister, cousin, brother-in-law, sister-in-law, son-in-law, daughter-in-law, son, daughter, nephew.
Gender can be easily inferred for the majority of these parental keywords. Figure 3 shows some general statistics on gender and age. It shows that, in this sample of our collection, patients are almost equally distributed according to gender, while most of the times (74.51%) the patient whose symptoms are reported by a parent author, are elder, as expected.

Figure 3: *Gender and age of patients who are relatives of a thread’s author*

## 4 Data Analytics: The social phenotype of diabetes

Data analytics in healthcare is evolving into a promising field that takes advantage of the increasing daily availability of health data to extract insights for producing better-informed decisions [18]. In this Section our objective is to show that, by analyzing the social phenotype of patients, *it is possible to derive insightful information on symptoms and complications that, in spite of their clinical severity, concern patients the most, and negatively affect their lives and their well-being*. This information is relevant also because it is provided by patients in a spontaneous way, according to their priorities, rather than in response to specific questions formulated by specialists (as for in Quality of Life assessments).
In what follows, data are analyzed in the light of research questions presented in Section 1.

4.1 R1: What are the main complications reported by patients for selected diseases? Which symptoms are more frequently reported by patients?

Figure 4 shows the frequency of the 14 main discussion topics listed in Appendix 1. As already anticipated in Section 3.3, 9 of these topics were found to correspond to common diabetes complications and risk factors [6][4], precisely: glycemia, hepato pathology/gastroenterology, gynecology, angi ology, cardiovascular complications, neurology, ophthalmology/orthopedics, andrology and endocrinology. The other topics are: symptoms/feelings, dietary issues, clinical tests and drugs, diabetes in general, various problems.

In [6] diabetic peripheral neuropathy (corresponding to our topic neurology) is indicated as the most common complication, affecting from 30 to 50% of diabetic individuals. The other most common complications are associated with cardiovascular problems (topics cardiology and angi ology), kidney (topic hepato pathology), foot and eye (topic ophthalmology/orthopedics). This order of relevance, however, is not reflected in Figure 4. The histogram shows that patients are eager to discuss their personal feelings, worries, and prevailing symptoms (topic symptoms and feelings) in the vast majority of messages. Besides symptoms, the most frequent topics concern glycemic complications (note in Appendix 1 that this topic also includes insuline and insuline-related terms), dietary problems, clinical tests and drug effects. Although these problems are not considered by diabetologists as representing a severe limitation of a patient’s life [9] except for the assumption of insulin, which is known to be a major cause of discomfort, at least in comparison with other symptoms affecting eyes, limbs and kidneys [4]. Figure 4 shows that indeed they are reported by patients as being a major cause of discomfort.

Since symptoms and feelings is the most frequent and populated topic, and it is also the most interesting in order to outline the social phenotype of diabetes, we further partitioned it into 10 subtopics, using a semi-automated procedure described more in detail in Appendix 2. The 10 sub-topics are: negative feelings, polyuria, polydipsia, polyphagia and obesity, drowsiness and tiredness, eye symptoms, cardiovascular symptoms, nerve and limbs symptoms, sexual disfunctions, nephropaty. Negative feelings have been further...
partitioned into: anger, sadness, stress, fear. The histograms in Figures 5 and 6 show the distribution of these sub-topics.

According to the latent topic modeling approach adopted in this paper, every message is a mixture of topics. We are here interested in understanding the correlation strength between these topics, and in particular, what types of symptoms are complained in relation with what types of complications. This is shown in the heatmap of Figure 7. To study the correlation, we use the Normalized Pointwise Mutual Information, NPMI. In general, symptom types show the highest NPMI values for related complications, as expected. For example, eye problems such as: blurred, out of focus, shadow, tarnished.. are the most frequently complained symptoms in patients discussing ophthalmology/ orthopedics complications (retinopathy, diabetic retinopathy, maculosis, etc.). Eating disorders or concerns (polyphagia and weight) are mentioned especially in relation with glycemic, gynecological and endocrinological complications. Negative feelings are pervasive in all messages, therefore they do not show a strong correlation with any specific complications, although neurology is shown to have some degree of correlation.
Figure 5: Percentage of occurrence of "symptoms and feelings" sub-topics in all threads

Figure 6: Relative incidence of "negative feelings" types
4.2 R2: Are there gender/age differences in a disease perception?

To answer this question, we considered our age and gender profiled sample of the data. In analyzing this data, we must keep in mind that, although presumably the patients' symptoms and complications are objectively reported by the authors of messages (i.e., the patients’ relatives), it is not possible to attribute negative feelings to either the patients or their relatives.

When considering the distribution of symptoms categories by age (Figure 8), we note that elder patients are more frequently reported to suffer or fear cardiovascular problems (tachycardia, heart attack, stroke) while adults are more concerned with eating disorders and overweight. Furthermore, when comparing Figure 8 with the distribution of symptoms in the total population (Figure 5), we may notice that the latter is more similar to the Adult/Young histogram than to the Elder histogram. This makes sense, since we can imagine that adults and young, more than elder patients, may decide to express their concerns on health-related on-line forums. Elders ”speak” in the words of their younger relatives.

When analyzing gender, we note no significant difference between males and females (Figure 9), except than for sexual disfunctions, which are men-
tioned significantly more frequently in association with male patients than females, although the incidence of these symptoms is low in both gendered samples. However, if we consider previous Figure 7 on symptoms by complications, a gender difference can be noted when comparing messages discussing andrological and gynecological problems. Patients with andrological disorders (presumably males) strongly fear about their sexuality, while patients with gynecological disorders (presumably females) show correlation with polyphagia and weight, sexual disfunctions (much less than males) and negative feelings.

4.3 R3: Does this ”patient-centric” study of a disease perception correspond to published results using traditional Quality of Life assessments?

In the past years there has been considerable research on health-related quality of life (QoL) assessments, motivated by the fact that clinical variables alone do not fully capture patients’ perception of their health [20]. Many of these studies focused on diabetes, like [17] [6] [4] and several others, due to the high diffusion of this disease. The typical way in which these studies are conducted is by administering a questionnaire to a sample of diabetic pa-
Figure 9: Percentage of occurrence of "symptoms and feelings" sub-topics in gender-profiled messages

Figure 10: Comparison of social phenotype of diabetes with two survey studies [6] [4]
tients with different features, e.g., with and without diabetic complications, type 1 or type 2 diabetes, demographics, etc. However, due to the difficulty of retrieving a large sample of patients, these studies have been able to consider only a subset of possibly influencing variables, in order to obtain sufficient statistical evidence.

A popular questionnaire is the MDQoL-17 [1][17][7]. Questions typically include frequency of pain types, worry types (e.g., missing work or diabetes complications), and satisfaction with social relationship, sexual life, current treatment, etc. The results however are rather contradictory. For example, the authors in [17] say that patients with Type 2 diabetes have a negative impact on their quality of life with or without complications. Instead, [7] found that the presence of complications or comorbidity conditions in Type 2 patients has the most significant influence on QoL of diabetic patients. In this regard, [1] observe that: ”because the selection of items was driven by the statistical item relationships provided by the participants in this study, the extent to which these participants and their responses are not representative of the general population of people with diabetes may limit the generalizability of the instrument”. In other terms, the small number of responders is the main limitation of the majority of QoL studies.

A much larger-scale experiment was presented in [4]. They present a 5-year observational study of individuals with or at risk for diabetes diagnosis, in which 15,794 questionnaires were returned. In this case, evidence was sufficient to partition responders in 4 different categories (low risk, high risk, type 1, type 2) and 6 demographic categories. The baseline survey consisted of 64 questions on health-related topics, including symptoms, comorbidities, family history, etc. A total of 13 symptom types were included in the questionnaire. The authors however report that, although some of these symptoms should be frequent in any diabetic patient, they were not reported by about 70% of the respondents: ”it will be important to determine whether this large pool of diagnosed but largely asymptomatic respondent [...] reflect earlier diagnosis and adequate symptom control through appropriate treatment or simply attention to the wrong symptoms” [4].

This is exactly the main added value of experiments like the one reported in this paper: patients are freely expressing their symptoms and concerns, without any bias possibly injected by doctors. Furthermore, symptoms’ types are automatically learned from patients’ generated texts, using topic detection techniques, rather than being defined a priori by doctors - a practice that does not facilitate a comparison among different studies, since different
questionnaires may list different symptoms. The second advantage is the dimension of the sample, that can easily reach very high numbers. The obvious disadvantage is that patients cannot be profiled in any way. Although, in future extensions of the present work, more refined text mining techniques can be used for larger-scale profiling, detailed profiling such as in [4] cannot be achieved.

Due to the previously outlined diversity of methodological instruments, a comparison among the results of this study and state-of-the-art QoL assessment is not fully appropriate, but we nevertheless attempted to compare our analysis on most frequently reported symptoms (Figure 5) with analogous statistics reported in [4] and [6], two studies in which the main considered symptoms are explicitly listed. To facilitate a comparison among different symptom labels, we manually identified associations (when appropriate) between symptoms’ labels used in these surveys and the ones used in our study. For example, we merged statistics on symptoms: “extreme hunger” and “unusual weight loss” in [4] and paired these symptoms with our sub-topic “polyphagia and weight”. Similarly, we aggregated heart attack, chest pain, coronary heat disease, congestive heart failure, stroke in [6] and paired with our topic “cardiovascular problems”. When reported data in surveys where partitioned according to patients’ demographic of disease categories (e.g., type 1 or type 2 diabetes), we computed a weighted average of the reported values. The result of this comparison is shown in Figure 10. Although statistics are rather different, it is worth noticing that symptoms types observed in our study correspond to those considered in survey studies, and that our study is more complete in this sense, because our list is the union of all symptoms reported in either [6] or [4]. We further note that dietary and weight issues are those for which there is the larger difference between survey studies and our social phenotype. It may seem surprising, but probably food restrictions constitute a daily and constant limitation of diabetic patients’ everyday life, and though not in itself serious, it is experienced with much discomfort.

\[\text{compare, e.g., [4] and [6]}\]

\[\text{note that shortness of breath and chest pressure are listed in [4], but although related words have been found in our topics, there was no easy way to associate these two symptom labels with our topic labels.}\]
5 Concluding remarks

In this paper we presented a study on diabetic patients’ quality of life, based on their freely expressed descriptions of the disease, symptoms and complications. Our study was conducted on a large sample of threads extracted from 4 popular Italian health blogs. Text classification and a state-of-the-art topic detection techniques have been used to derive what we called the “social phenotype” of a disease. Although the idea of extracting the digital phenotype of diseases (a broader concept that includes the social phenotype) has been launched in [9], to the best of our knowledge, this is the first large-scale study in which the utility of this approach is demonstrated.

The main findings of our study can be summarized as follows:

1. The most frequent topics discussed by patients are their negative feelings (which are pervasive in almost all messages), followed by (hyper-)glycemia and insulin-related issues, dietary issues, and clinical tests. Often, these issues - especially diet restrictions and clinical tests - are not considered in QoL questionnaires, since they are not perceived by doctors as representing severe limitations. Our data show that instead, diet, glycemic control, drugs and clinical tests have a negative and daily impact on patients’ life, and they are discussed more frequently than common and severe diabetic complications [4], such as problems with kidneys, eyes and limbs.

2. Elder patients mostly fear, or suffer, cardiovascular symptoms (frequent keywords are: tachicardia, beating..) while adult and younger patients are concerned with polyphagia and alimentary disorders (frequent keywords are: hungry, appetite, put on weight, lose weigh...).

3. We found no significant difference between females and males, however females affected by gynecological complications fear overweight and express discomfort (negative feelings), while males affected by andrological complications are mostly worried about sexual disfunctions.

Because it is impossible to accurately profile patients, the social phenotype of a disease is complementary, not substitutive, of traditional QoL questionnaires. However, it presents a number of advantages with respect to state-of-the-art survey studies:
1. The dimension of the sample is much larger in comparison with responders of questionnaires. In the present study we paid much attention to the precision of classified messages (see Section 3.2) in spite of recall, and in addition, we restricted to health blogs in Italian, which eventually led us to collect a dataset of 40443 patients’ messages. Extending this study to English blogs could easily increase the dataset by one order of magnitude, or more. Note however that the Italian sample (as remarked in Section 3.1) represents the typical profile of industrialized nations.

2. Survey studies can hardly be compared with each other, because the types of considered symptoms in questionnaires may be different, and demographic profiles of patients are also different. Instead, the social phenotype "objectively" collects and cluster complications, worries, symptoms and feelings, just as they are expressed in the patients’ words. It reflects the reality of patients' everyday life, and how they perceive their disease, without any preconception or influence injected by medical knowledge. This has led to a number of surprising findings, but also to a number of expected findings (for example, 9 of the automatically detected topics were found to correspond to main known diabetes complications), to confirm the accuracy of the adopted text mining techniques.

Acknowledgments

This work was supported in part by the MIUR under grant “Dipartimenti di eccellenza 2018-2022” of the Department of Computer Science of Sapienza University.

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**Appendix 1: Lists of topics**

The 14 extracted topics are listed below in descending order from the most common to the least predominant in the collection. For all the topics, only the most significant terms are reported in order of importance. All terms are translated from Italian to English for readability. Furthermore, since words are represented in LDA as multinomial probability distributions over topics, there are overlapping words in different topics.

Topic labels have been manually assigned, however no manual correction of terms in topics has been performed: although topics may include some apparently less related terms, they reflect similarity of contexts according to the topic model described in Section 3.3. For example, note that terms such as *insulin, infection* and *surgery*, although they are neither symptoms nor feelings, have been associated to the topic SYMPTOMS-FEELINGS. Since topics are generated by contextual similarity and co-occurrence, this clearly shows that patients are emotionally affected by, and fear, insulin, infection and surgery.
(ID=1) **SYMPTOMS-FEELINGS**: [symptoms, pain, weight, pressure, insulin, anxiety, stress, fear, diet, glycemia, obese, low, leg, burning, annoyance, feeling, fatigue, feeding, attack, tiredness, nausea, overweight, cramp, malaise, dizziness, fat, weariness, tachycardia, crisis, hypertension, sleep, slimming, sweat, hyperglycemia, swelling, sting, metabolism, heart, psychology, cardiac, metformin, surgery, hypoglycemia, hair, erection, cold, eyes, tremor, infection, skin, inflammation, effort, thyroid, panic, nervous, hyper-cholesterol];

(ID=2) **GYNECOLOGY**: [gynecology, cycle, ovary, pregnancy, pill, hormonal, polycystic, polycystic ovary, gynecology obstetrics, prolactin, ovule, progesterone, fsh, abortion, testosterone, menstruation, tsh, dosage, follicle, acne, estradiol, hormone, amenorrhea, endocrinology, insulin resistant, micropolistic, insulin, hormone dosage, beta, micropolistic ovary, pregnant, hirsutism, follicle, metformin, cortisol, acid folic, ovary, mui, contraceptive, insulinemic, menopause, thyroid, dhea, ovary syndrome, delay, pcos, endometrium];

(ID=3) **DIET**: [diet, food, meal, fruit, vegetable, carbohydrate, sugar, bread, ferritin, lunch, meat, fat, hunger, digestive endoscopy, gastroenterology endoscopy, sweet, breakfast, milk, biscuit, nutrition, fish, integral, lymphocytes, globules, neutrophils, coffee, protein, dinner, consuming, diarrhea, monocyte, eosinophile, iron, foods, oil, weight, slice, anemia, intolerance, celiac disease, glycemia, mch, mcv, rice, cheese, acid, vitamin, mchc, fruit vegetable, honey, platelets];

(ID=4) **GLYCEMIA**: [glycemia, curve, glucose, diabetology, fasting, metabolism, diabetology metabolism, glycemic curve, basal, insulin, fasting blood sugar, hemoglobin, load curve, diabetes, glycated, insulinemic, glucose metabolism, glycated hemoglobin, gestational, gestational diabetes, diabetes metabolism, glucose charge, analysis, basal glycemia, diet, glycosylated, meal, glycosylated hemoglobin, sweet, insulin glycemia, weight, glycaemia analysis, fasting glucose, urine, diabetes blood sugar, diabetes endocrinology, blood sugar, sugar, high, blood sugar insulin, low blood sugar, nutrition, glycemic load, diet weight, basal insulin, breakfast, blood test, glucose urine, hyperglycemia];

(ID=5) **CLINICAL TESTS**: [cholesterol, triglycerides, hdl, analysis, cholesterol hdl, ldl, blood, creatinine, urine, transaminase, gamma,
gpt, bilirubin, high, high cholesterol, proteins, got, cholesterol triglycerides, azotemia, hemoglobin, glycemia, tot, blood analysis, ast, ldl cholesterol, cholesterol glycemia, hdl triglycerides, leukocytes, psa, glucose, albumin, hematology, blood cholesterol, ketones, uric, hdl ldl, nephrology, uric acid, uricaemia, statin, globulin, ves, amylase, blood count, cholesterol analysis, got gpt, urinalysis, potassium, urea, alpha, creatininemia, gpt, glycate, urobilinogen, phosphatase];

• (ID=6) **HEPATOLOGY/GASTROENTEROLOGY**: [hepatology, gastroenterology, liver, hepatic, urine, liver hepatology, gastroenterology liver, renal, pancreas, pancreatic, abdomen, ultrasound, kidney, steatosis, calculus, urinary, urination, tumor, cirrhosis, tac, bladder, gallbladder, nephrology, prostate, kidney, lesion, liver cirrhosis, focal, liquid, abdominal, spleen, lung, abdomen ultrasound, diameter, fatty liver disease, infiltration, insipid diabetes, cysts, colic, bile, biliary, infection, lymph node, carcinoma];

• (ID=7) **ANGIOLOGY**: [cardiology, artery, stenosis, carotid, hypertension, ecg, angiography, aortic, valve, vascular, coronary, heart, mitral, ventricular, vascular surgery, plaque, atheromasia, carotid, calcification, ischemia, echo-doppler, cardiac surgery, doppler, heart attack, dilated, cardioaspirin, diabetes hypertension, vascular angiography, echocardiogram, electrocardiogram, cardiac, flow, coronarography, thickening, angioplasty, venous, vessels, parietal, femoral, anterior, hypertensive, cardiopathy, chest, mellitus, systole, diabetes mellitus, bilateral, smoker, arterial hypertension, hypertrophy, occlusion, vertebral, cardiovascular];

• (ID=8) **DIABETES**: [diabetes, diabetes endocrinology, diabetes endocrinology, mellitus, metformin, diabetology, diabetes mellitus, lunch, diabetic, dinner, insulin, glycemia, dinner lunch, microalbuminuria, curve metabolism, diabetes blood sugar, lantus, diabetes diet, breakfast lunch, breakfast, metforal, prandiale, diet, glycemic level, diabetes insulin, hypoglycemia, glucophag, meal, glycated, basal insulin, fasting, mini-curve, pellets, peptide, nutrition, weight, diabetes analysis, fasting glycemia, sugars, obesity, insulin-dependent, glycated hemoglobin, weight height, cpr, metabolic, proteinuria, postprandial, machine, dose, weight loss, pressure, hemoglobin, hyperglycemia, novonorm, kcal, glucose, carbohydrate, cholesterol, insulin resistant, triglycerides, glycosyl,
triatec, glicid, insipid, simvastatin, ramipril, lasix]

- (ID=9) **VARIOUS_PROBLEMS**: [dermatology, disability, cortisone, venereology, dermatology venereology, legal, psychiatry, cataract, anesthesia, drops, cream, radiotherapy, hernia, mellitus, transplant, diabetes mellitus, plant, aneurysm, fever, depression, neurosurgery, smoking, bacterium, reanimate, cutaneous, lumbar, carrier, immunology, xanaz, apnea, hypoglycemic, remedy, allergology, recognize, coma, aggravated, allergy, diabetes, psoriasis, antihistamine, marrow, oral, ability, polyneuropathy, transfusion, sleepy, lesion, neuropathy, orthopedics, heart disease, carcinoma, immunosuppressant, Alzheimer];

- (ID=10) **NEUROLOGY**: [neurology, neuropathy, pain, tingling, resonance, encephalon, orthopedics, ischemia, rmn, cerebral, geriatrics, ankle, arthritis, tac, magnetic, rheumatology, leg, fingers, magnetic resonance, nerve, arm, limb, knee, rheumatoid, diabetes, dementia, Parkinson, diplopia, stroke, vascular, ventricular, hand, ambulate, atrophy, sub-cortical, back, arthrosis, occlusion, unstable, dizziness, frontal, hypertension, bilateral, head turning, memory, brain, swelling, hip, injury, cephalus, physiotherapy, vascular, motor, suffering, amplitude, hypertensive, fracture, muscle, limb, articular, micro, heart disease, skull, ear, anterior, microcyst, femur, ophthalmology, cranial, emisom, paresthesia, mesencephalon, occipital, cerebellum, hemisphere];

- (ID=11) **CARDIOLOGY**: [heart, cardiovascular, cardiovascular heart, pressure, heart attack, aorta, respiratory, heart breathing, hypertensive, cardioaspirin, cardiologist, heart disease, coronary, diabetic hypertension, hypertension, diabetes, triatec, erectile dysfunction, norvasc, glycosuria, angioplasty, artery, cardiac, vasculopathy, angina, plavix, arterial pressure, coronography, stent, senile, ictus, torvast, low pressure, prevention, diabetes, rhythm, anticoagulant, pharmacological, hereditary, bypass, ischemia, cerebral, lobivon, mellitus, diabetes mellitus, prevention, cardiovascular, peripheral, arterial hypertension, smoking, cholesterol, insulin diabetes, atheromasia, coronary artery disease, hypertension, hypercholesterolemia, arteriopathy, dyslipidemia, ima, arteriosclerosis, dilatrend, coumadin, ticlopidin, lopresor, ramipril, enapren, congescor, tenormin, aprovel, cardirene, atenolol, nebiloz, blopress, ascriptin, micardis, antiperstens, cerebrovascular, cardura, seloken];
(ID=12) **OPHTHALMOLOGY/ORTHOPEDICS**: [eyes, oculist, oculus, foot, retina, retinopathy, diabetic retinopathy, laser, maculosis, wound, injection, degeneration, myopia, surgery, edema, hallux, circumcision, glaucoma, fluorangiography, plastic, amputation, insulin mellitus, thrombosis, optical, cicatrization, dark, fistulas, procedure, opening, patch, puncture, surgery, fingers, local, lenses, calf, radius, see, operative, vitreous, close, blind, canal, opaque, wrist, resorption, healing, dot, swelling, vitreous, temporary, ischemia, myodesopsie, holes, hole, iris, cornea, perforator, corneal, scar, cataract, vitrectomy, crystalline, suture, fissure, flap, gangrene, peripheral];

(ID=13) **ENDOCRINOLOGY**: [nutrition, biochemistry, hormone glands, gland, hormone, endocrinology, endocrinology glands, slimming, sideraemia, thyroid, hypothyroid, eutirox, dietology, plasmaticot, basal blood sugar, weight gain, glucose glucose, tsh, mcg, hyperthyroid, glycemic load, insulin glycemia, thyroid endocrinology, diet, psychotropic, kcal, weight, phosphorus, chemiluminescent, diet, tapazol, absorption, diet nutrition, glycemic curve, insulinemic curve, cortisol, intake, weight height, hct, chili, diabetes endocrinology, tpo, glycemia analysis, integral, insulin, prandial, resistant insulin, resistant, thyroglobulin, glycemia diet, pharmacology, hunger, bilirubin, tirosint, tiroxin, levotiroxin, metformin, triglycerides, cholesterol, ths, ferritin, parathormone, tyrosine, prolactin, hypocaloric, prolactinemia, cholesterolemia, metforal, dosage, metabolism, glyco, homocysteine];

(ID=14) **ANDROLOGY**: [andrology, erection, sexual, glans, cialis, testosterone, ejaculate, viagra, impotent, urology, libido, morning, masturbation, critical, hyperglycemia, decline, sex, occasional, inhibitors, male, partner, erectile, reach, ace, emotional, timetable, precocious, nocturnal, psychology, rigid, approach, depression, extreme, auto-erotic, excited, orgasm, erectile, vardenafil, misfire, sildenafil, tadalafil, virile, enduring, eroticism, lust, embrace, vigor, excitatory].
Appendix 2: Sub-topics of the topic "Symptoms"

The topic SYMPTOMS-FEELINGS is the most important for the purpose of characterizing the social phenotype of diabetes. For this reason, words in this cluster have been further partitioned into 10 sub-topics and enriched in a semi-automated manner:

1. First, we manually identified some semantically related terms of the initial SYMPTOMS-FEELINGS topic, creating ten small initial clusters (each cluster consisted of four or five terms).

2. With Word2Vec, we obtained the vector spaces representing the starting clusters.

3. With Word2Vec, we selected the terms of the collection most similar to the starting clusters (with a similarity score of at least 0.80 w.r.t. the cluster vector spaces) and we added these words to the ten clusters.

The ten symptom-feelings sub-clusters are:

- **NEGATIVE FEELINGS**: [fear, anxiety, stress, worry, pain, frustration, depression, unnerved, terror, dissatisfaction, melancholy, discomfort, paranoia, anger, sadness, loneliness, anguish, bad mood, impatience, restlessness, insecurity, unhappy, disappointment, discouragement, drama, exasperated, overwhelmed, worn down, unmotivated, resentment, hatred, sad, apprehension, repressed, displeasure, tragedy, malaise, angry, restless, oppressive, destabilized, crying];

- **POLYURIA (URINE)**: [urine, polyuria, pis, pee, peeing, urination, mingle, bladder, pollakiuria, nocturia, voiding, dripping, dysuria, hematuria];

- **POLYDIPSIA (THIRST)**: [polydipsia, thirst, drought, drink, glass, liter, sip, rasp, water, cup, drink, beverage, swallow, gulp];

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\[13\] as before, labels have been added manually, and cluster members have been translated in English
- **POLYPHAGIA AND WEIGHT**: [polyphagia, hungry, appetite, put on weight, lose weight, overweight, underweight, obese, weight, fat, thin, pounds, skinny, kilo, heavy, slender, waist, belly, hyper-caloric, greedy, body, skinny, kcal, hypo-caloric, glutton, BMI, long-limbed, decay, eat];

- **DROWSINESS AND TIREDNESS**: [sleep, sleepy, tired, weak, exhausted, dazed, heavy, dizzy, very weak, breathless, fatiguing restlessness, listlessness, weakness, perennial, malaise, nausea, numbness, heartbeat, weakened, listless, out of breath, breathless, tiring, weary, jaded, worn];

- **EYE PROBLEMS**: [eye, retina, retinopathy, tarnished, blurred, sight, low vision, visually impaired, blind, monocular, maculosis, maculopathy, visus, sight, glaucoma, scotoma, monocle, shadow, glow, out of focus, amblyopia, cataract, vitreous];

- **CARDIOVASCULAR PROBLEMS**: [beating, tachycardia, hypertension, pressure, heart attack, stroke, heart, cardiovascular, thrombosis, artery, vein, cardiopathy, thrombus];

- **NEUROPATHY AND LIMBS**: [neuropathy, nerves, peripheral, limb, foot, leg, hand, amputation, forearm, calf, thumb, wrist, little finger, arm, elbow, ankle, big toe, thigh, paraesthesia, heel, palm, finger];

- **SEXUAL DYSFUNCTION**: [dysfunction, erectile, erection, sexual, impotent, viagra, cialis, levitra, libido, libidine, sildenafil, tadalafil, vardenafil, orgasm, eroticism];

- **NEPHROPATHY (KIDNEYS)**: [nephropathy, kidney, renal, microalbuminuria, proteinuria, creatinine, hydronephrosis, glomerulus, albuminuria, proteinuria, creatininemia, nephritis, monorenes, GFR, microhematuria, chronic renal failure, bacterium, glomerulonephritis, nephrology, clearanec, pielectasia, pielonefrite].