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Model for identifying the characteristics of an individual from a class of comments

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ABSTRACT: Judgments made on a subject by certain people can take various forms. In the case of the covid-19 crisis, certain opinions on the vaccine for this pandemic have generated a lot of comments of various kinds. Unfortunately, some of them have some side effects that vary from person to person. This phenomen on creates then feelings of caution in the population not yet vaccinated. The objective of this article is to propose a model allowing us to analyze and understand the characteristics of the categories of people who made these comments. This model identifies individuals based on the classes of comments issued. It is based on a hybrid approach combining the multinomial logistic model and a genetic model. An application is made on the data of the comments of the Covid-19 in Côte d'Ivoire.

KEYWORDS: Multinomial logistic model, Genetic model, Commentary, Automatic classification, Covid-19.

1 INTRODUCTION

Covid-19 has infected more than six hundred million people worldwide [1]. In order to fight this pandemic, all scientific communities have mobilized to make their contribution. This mobilization gave rise to several categories of vaccines including Pfizer, Moderna, Astra Zeneca etc [2]. These vaccines like the others are not without effects. Some of these effects are presented in the work of Jonathan Sprent et al. and mainly concern fever, headaches, fatigue, etc [3]. It appears that these effects differ not only from one vaccine to another, but also from one individual to another. With the evolution of technology and the appearance of social networks we are witnessing a rapid spread of large quantities of comments on different vaccines in various forms [4], [5], [6]. However, these can constitute a real lever of controversy and frighten some people. Clarifying these doubts among the populations then becomes an obligation to curb the spread of these comments. In view of all the above, one wonders how identify comment classes? What characteristics of people for each class of comments?

The objective of this article is to propose a model allowing us to analyze and understand the characteristics of the categories of people who have made comments. To do this, we have structure this work in three (3) parts. The first takes stock of the work on covid-19. The second consists of the presentation of the methodological approach and the exploitation of these data. Finally, present the results obtained from this operation.

2 STATE OF THE ART

The COVID 19 vaccines have generated several comments due to the side effects they presented in some. These opinions are diverse and vary from one individual to another depending on the appearance of new comments. Indeed, some relate to the causes and others to the mode of transmission. Among these we can cite that of LAPIERRE et al. and BANIASAD et al. which addresses all aspects related to the functioning of the Covid-19 disease [7], [8]. In this work, the authors mainly address the modes of transmission, the methods of diagnoses then potential treatments through the clinical picture and the principles of prevention of transmission. Among these authors, others focus on the mechanism and strategy for creating a vaccine in order to slow the spread of the disease by reducing the risk of contamination [9], [10]. However, the birth of these vaccines has not left the whole world indifferent. This has manifested itself in several acts including vaccine hesitancy. Mohammad S Razai in his article on Covid-19 Vaccine Hesitancy defines vaccine hesitancy as "a delay in accepting or refusing safe vaccines despite the availability of vaccination services" [11]. He presents this reluctance as a universal problem. Indeed, surveys conducted in 2021 report that between 50% and 60% of all respondents worldwide would be willing to receive a Covid-19 vaccine and the causes of this refusal are multiple [12], [13]. A UK "Understanding Society" survey shows that 42.7% of people were reluctant due to unknown future effects, 11.4% due to side effects and 7.6% due to lack of confidence in vaccines [14] [15]. It is clear that vaccine hesitancy is related to immediate or future comments about side effects. According to WHO, "a side effect is a harmful and unwanted reaction appearing after the use of a health product respecting the doses normally used in humans" [16], [17]. These effects can be disturbing and have been the subject of several comments in the press as well as on social networks [18]. For a good management of these comments, a classification is necessary and is made according to several criteria. These criteria are presented in the article by El Bouazzi et al. and are as follows: Classification according to frequency, classification according to the nature of ADRs, classification according to the mechanism of occurrence, classification according to predictability, classification according to preventability and classification according to severity, classification according to organ class [19]. Classification therefore appears to be a useful approach in understanding comments relating to side effects. This is confirmed in the work of Courcoul et al. on the classification of drug side effects [20]. In fact, in this work they use Natural Language Processing (NLP) to set up "a binary classification model to detect tweets containing a drug name which highlight a side effect. ". This study ends with conclusive results, 92% accuracy rate. Classification is therefore an approach widely used in the scientific field, particularly on side effects.

Most studies in the literature certainly present the effects of covid-19, without however making a correlation between the individual characteristics of people and the classes of comments. Hence the interest of this study.

3 MOTHODOLOGICAL APPROCH AND MODELING

3.1 MOTHODOLOGICAL APPROCH

The architecture of the proposed model is presented in the Figure1. as following:

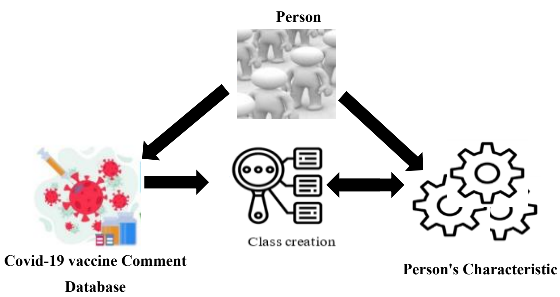

Fig. 1. Model architecture

This architecture consists of (03) three levels, namely:

(a) The knowledge base of comments made on Covid-19 vaccines.

It contains the comments collected by individual on the vaccines.

(b) The phase of creating classes by category of comments.

Based on the comments collected, the class categories were designed.

(c) The phase of associating people's characteristics with comment classes. This phase consists of identifying the characteristics of individuals and associating them with each category of comments.

4 MODELIZATION

4.1 CREATING CLASSES

Let X, the set of available comments designating the knowledge's base.

From this base, we develop classes $C_{i,1<i<M}$ of comments, where the set of which is denoted $\Pi^{(M)}$ as follows:

$$\Pi^{(M)} = \{C_1, \ldots, C_M\} \tag{1}$$

Each class $C_{i,1<i<M}$ is associated with a set of comments $x_i \subset X$.

Let x_{new} a new set of comments. And, noted C_{new}, the associated class, we have:

$$\Pi^{(M)} = \Pi^{(M-1)} \cup C_{new} \tag{2}$$

These new comments of x_{new}, can also belong to existing classes, in addition to the class C_{new}. Our approach therefore consists to propose a model for integrating these new comments into existing classes.

Suppose the class C_i is created by a classification model training function $\psi_M \subseteq \mathfrak{I}$. The dynamic partition $\Pi^{(M)}$ as well as the classification model $\mathfrak{I}^{(M)}$ can be defined by:

$$\Pi^{(M)} = \{C_1, \ldots, C_M\} \tag{3}$$

$$\mathfrak{I}^{(M)} = \{\psi_1, \ldots, \psi_M\} \tag{4}$$

With

$$\forall\, x_{new} \in C_{new},$$

$$P(x_{new} \in C_i) = \alpha,\ \psi_M(x_{new}) - \mu_a \geq 0, \tag{5}$$

where, $\alpha, \mu_a \epsilon [0,1]$

4.2 IDENTIFYING CHARACTERISTICS

In the context of identifying characteristics c, let us denote ind, an individual in a class C. Let us suppose that each ind belongs to a single class $C_{i,1<i<M}$. This membership is reflected by the characteristic c_{ind} of ind which is worth $C_{i,1<i<M}$ if:

$$ind\ \epsilon\ C_{i,1<i<M} \tag{6}$$

For an individual ind, we define the probability ρ of belonging to the class $C_{i,1<i<M}$ knowing the set of comments $X_{C_{i,1<i<M}}$ involved in the development of the class $C_{i,1<i<M}$:

$$\rho(C_i = C|X_{1i}) = \frac{exp(\mathcal{E}_{0C} + X_{1i}^T \mathcal{E}_{1C})}{\sum_{l=1}^{card(X)} exp(\mathcal{E}_{0l} + X_{1i}^T \mathcal{E}_{1l})} \tag{7}$$

With X_{1i}^T, a specific comment.

Supposing $\mathcal{E}_{0C} = 0$ and $\mathcal{E}_{1C} = 0$ so that the number of comments $card(X)$ becomes the comments reference for feature identification.

In general, the first X_{1ind} comments are included in the multinomial logistic model when one wishes to create or interpret the classes based on these comments. Most often having no a priori on the constitution of classes, no comments are added to the model in practice. It becomes π_{iC} :

$$\rho(C_i = C|X_{1i}) = \frac{exp(\mathcal{E}_{0C})}{\sum_{l=1}^{card(X)} exp(\mathcal{E}_{0l})} \tag{8}$$

4.3 ASSOCIATION (FEATURES - COMMENT CLASS CATEGORY)

The proposed approach is modeled on the functioning of a genetic model which explains the genesis of a performance P to an elementary observation in the form of:

$$P = G + \Pi^{(M)} \tag{9}$$

With G, the number of characteristics of an individual ind and the performance P represents the probability of observing a characteristic c in a class $C_{i,1<i<M}$ of comments such as $P \in [0,1]$. By hypothesis, these two elements are independent.

By applying the previous equations (8) and (2), we have:

$$P = \sum_{i=1}^{G} \sum_{l=1}^{Card(X)} \left(\frac{exp(\varepsilon_{0C} + X_{1i}^{T}\varepsilon_{1C})}{\sum_{l=1}^{card(X)} exp(\varepsilon_{0l} + X_{1i}^{T}\varepsilon_{1l})} + \Pi^{(t-1)} \cup \{C_{New}\}\right) \tag{10}$$

5 Simulation and Results

As part of this study, we used the database of comments from people vaccinated against Covid-19 in Côte d'Ivoire.

This database is essentially made up of comments on vaccines from the Pasteur Institute of Côte d'Ivoire. These data consist of 48,110 observations and 11 variables as represented in figure 2 below.

	VAERS_ID	SYMPTOM1	SYMPTOMVERSION1	SYMPTOM2	SYMPTOMVERSION2	SYMPTOM3	SYMPTOMVERSION3	SYMPTOM4
1	0916600	Dysphagia	23.1	Epiglottitis	23.1	NA	NA	NA
2	0916601	Anxiety	23.1	Dyspnoea	23.1	NA	NA	NA
3	0916602	Chest discomfort	23.1	Dysphagia	23.1	Pain in extremity	23.1	Visual impairment
4	0916603	Dizziness	23.1	Fatigue	23.1	Mobility decreased	23.1	NA
5	0916604	Injection site erythema	23.1	Injection site pruritus	23.1	Injection site swelling	23.1	Injection site warmth
6	0916606	Pharyngeal swelling	23.1	NA	NA	NA	NA	NA
7	0916607	Abdominal pain	23.1	Chills	23.1	Sleep disorder	23.1	NA
8	0916608	Diarrhoea	23.1	Nasal congestion	23.1	NA	NA	NA
9	0916609	Vaccination site erythema	23.1	Vaccination site pruritus	23.1	Vaccination site swelling	23.1	NA
10	0916610	Rash	23.1	Urticaria	23.1	NA	NA	NA
11	0916611	Blood pressure decreased	23.1	Chest pain	23.1	Chills	23.1	Confusional state

Fig. 2. Database in Rstudio

The variables of the array elements consist of:

- **VAERS_ID:** Identifying people who made secondary comments about the vaccine he received;
- **SYMPTOM1:** Comments related to the first version of the vaccines received by an individual i;
- **SYMPTOMVERSION1:** Version of the first vaccine of the first dose received;
- **SYMPTOM2:** Comments related to the second dose of the first vaccine received by an individual i;
- **SYMPTOMVERSION2:** Version of the first vaccine of the second dose received;
- Etc.

The R programming language has been in the results implementation phase. Data analysis was possible thanks to the readr packages for importing our data, and FactoMineR for automatic classification.

5.1 Results

The results are presented here:

Result 1: word cloud.

We processed and set up the word cloud from the corpus as shown in Figure 3 below. This cloud is made using the R language wordcloud package.

Fig. 3. The Corpus's Word cloud

Thanks to the result of this cloud, we observe more frequent, medium frequent and infrequent words. We can cite among others the word Pain which is the most frequent. Then, the words Site, injection, blood, headache which are moderately frequent and those made up of chills, fatigue, normal. Then come test, heart, body which are the least common. The figure4 below gives us the frequency of the first ten (10) most frequent words in our corpus with a frequency of 8735 for the word "bread".

```
                word freq
pain            pain 8735
site            site 6317
injection  injection 5875
headache    headache 4750
blood          blood 4618
chills        chills 3912
fatigue      fatigue 3744
normal        normal 3525
test            test 3106
increased  increased 3100
```

Fig. 4. Word Frequency

<u>RESULT2 :</u> DATA CLASSIFICATION

The idea is to group each similar comment together to form comment classes. We therefore calculated the weighting by term frequency - inverse document frequency with the (tm) package of R before doing the classification. Then, we used the factorial coordinates of the PCA with the package (FactoMiner) and its HCPC function. It allowed us to perform CAH hierarchical ascending classification while keeping the default arguments. The execution gave us the following figure5 dendrogram with the number of clusters.

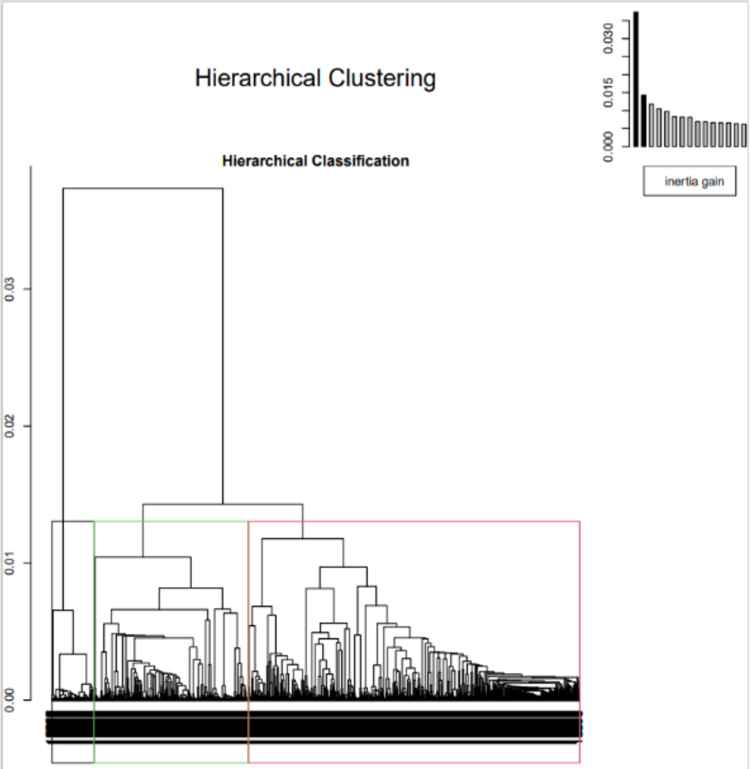

Fig. 5. Clusters 's dendrogram

This dendrogram gives us an idea of the number of classes or categories that the corpus of comments may contain.

Console ~/

$`1`

	v.test	Mean in category	Overall mean	sd in category	Overall sd	p.value
site	122.194422	0.4941290031	6.198506e-02	0.161615186	0.161123653	0.000000e+00
injection	120.610779	0.4938605619	6.043026e-02	0.189621477	0.163725151	0.000000e+00
warmth	64.016585	0.0871778575	9.224893e-03	0.149066531	0.055478203	0.000000e+00
erythema	58.538913	0.1402893448	2.644668e-02	0.141938331	0.088601824	0.000000e+00
pruritus	39.661269	0.1035358152	2.340114e-02	0.145046283	0.092052619	0.000000e+00
swelling	37.063899	0.1091766361	2.931353e-02	0.132383947	0.098169678	1.072583e-300
induration	36.073242	0.0566895367	8.115159e-03	0.141806198	0.061348552	5.960949e-285
bruising	19.965103	0.0174997404	2.175069e-03	0.098698846	0.034970503	1.107988e-88
vaccination	17.788404	0.0440618653	9.368888e-03	0.221090260	0.088856015	8.692029e-71
mass	16.214171	0.0261838182	5.541760e-03	0.113798078	0.058001671	4.004475e-59
pain	16.196440	0.0960873815	6.158074e-02	0.100256733	0.097065618	5.343253e-59
rash	14.303619	0.0605850692	2.259072e-02	0.172796823	0.121019502	2.077216e-46
reaction	14.169934	0.0351960047	1.266603e-02	0.109961008	0.072439441	1.406320e-45
cellulitis	12.790014	0.0173675706	3.613636e-03	0.102916685	0.048993468	1.864401e-37
nodule	11.928401	0.0127323607	2.228322e-03	0.083493961	0.040119578	8.417510e-33
urticaria	8.671348	0.0224004934	8.349923e-03	0.104278091	0.073822647	4.270361e-18
inflammation	7.975958	0.0113629237	3.360351e-03	0.079743306	0.045711872	1.512028e-15
streaking	7.388281	0.0031910696	3.860005e-04	0.046755725	0.017297464	1.487397e-13
indentation	7.173102	0.0023923184	2.406497e-04	0.043029335	0.013666291	7.331733e-13
lymphadenopathy	6.395314	0.0240074385	1.222553e-02	0.111636503	0.083933653	1.602181e-10

Fig. 6. List of group 1 comments

Subsequently, a factor Map is generated giving us more details on the number of comment class categories which we have in the following figure.

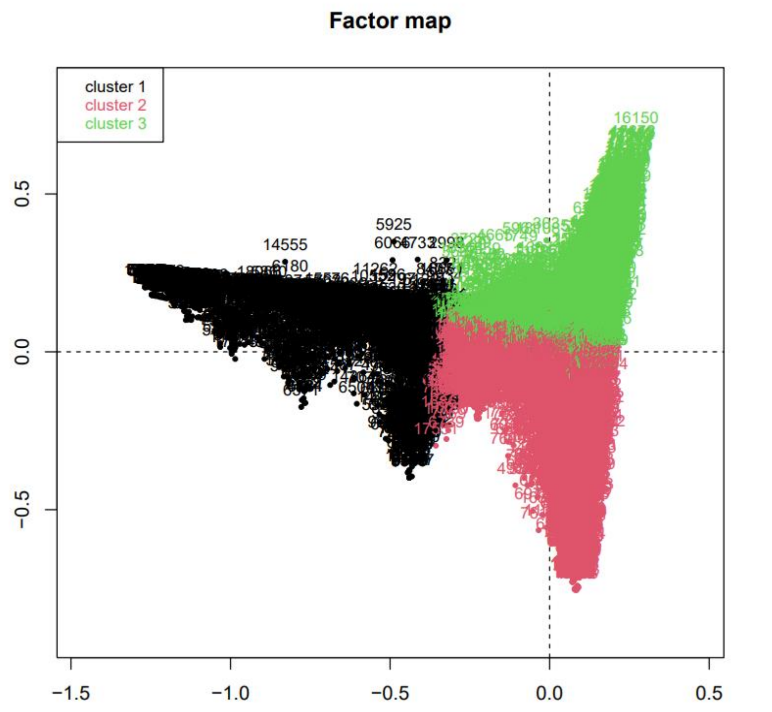

Fig. 7. Our clusters under Map factor

5.2 Class Descriptions

The classification allowed us to have three homogeneous classes described as follows:

- Class1 contains more “site and injection (site, injection)” comments.

```
> result_clust$desc.var$quanti
$`1`
              v.test Mean in category Overall mean sd in category Overall sd      p.value
site        122.194422     0.4941290031 6.198506e-02     0.161615186 0.161123653 0.000000e+00
injection   120.610779     0.4938605619 6.043026e-02     0.189621477 0.163725151 0.000000e+00
```

Further analysis shows that the comments “sites and injection” are more correlated with the comments “erythema, warmth, pruritus, induration and swelling”.

- Class 2 contains a large number of comments such as "headaches and Frisian (headache, chills)”.

```
              v.test Mean in category Overall mean sd in category Overall sd      p.value
headache     59.843282     1.069012e-01 0.0538367311     0.124355255 0.10011165  0.000000e+00
chills       57.294116     1.072348e-01 0.0519282929     0.140695310 0.10898397  0.000000e+00
```

- Class 3 contains more “blood” comments.

```
$`3`
              v.test Mean in category Overall mean sd in category Overall sd      p.value
blood        49.507592     0.0853586370 0.0427953191     0.151787157 0.115319133 0.000000e+00
```

5.3 Interpretation of classes

The first group contains more site and injection comments which are more correlated with the “erythema, warmth, pruritus, induration and swelling” comments. This means that group 1 contains more people with side effects of bruising, redness and swelling at the injection sites. Thus, given their similarity, vaccinated people having a side effect from this list are more likely to have other side effects from this same class. Figure 6... shows group 1 containing comments of similar side effects.

The second group contains more of comments "headhache and chills". Which means people in this group have more headaches and tinnitus after receiving the vaccine. Also vaccinated people with one side effect from this list are more likely to have the other side effects. Figure8 shows group 2 containing comments of similar side effects;

$`2`

	v.test	Mean in category	Overall mean	sd in category	Overall sd	p.value
headache	59.843282	1.069012e-01	0.0538367311	0.124355255	0.10011165	0.000000e+00
chills	57.294116	1.072348e-01	0.0519282929	0.140695310	0.10898397	0.000000e+00
fatigue	50.197399	9.657320e-02	0.0492710486	0.137953146	0.10638885	0.000000e+00
pain	47.487295	1.024076e-01	0.0615807371	0.117205143	0.09706562	0.000000e+00
nausea	40.505726	8.257395e-02	0.0410989962	0.158260750	0.11560217	0.000000e+00
myalgia	35.917164	7.133408e-02	0.0333333418	0.170019151	0.11945008	1.648532e-282
pyrexia	33.873967	7.210181e-02	0.0373815332	0.159323326	0.11572135	1.610801e-251
arthralgia	32.987267	6.567613e-02	0.0320766713	0.161736095	0.11499590	1.236785e-238
extremity	30.141423	4.961995e-02	0.0247708260	0.130423091	0.09307731	1.389518e-199
temperature	22.063324	3.242117e-02	0.0165130531	0.114633694	0.08140371	7.115665e-108
diarrhoea	21.643250	4.208589e-02	0.0220494666	0.145911288	0.10451874	7.036431e-104
body	20.427751	3.216548e-02	0.0173508116	0.112653062	0.08187813	9.476820e-93
feeling	19.285482	4.490007e-02	0.0272307889	0.135825173	0.10343914	7.112374e-83
dizziness	18.012945	5.312779e-02	0.0362004100	0.132632978	0.10609662	1.542014e-72
malaise	17.023619	3.449223e-02	0.0197010359	0.132900853	0.09809524	5.487221e-65
23.1	16.770533	1.317550e-01	0.1203267803	0.087491125	0.07693599	4.008968e-63
hyperhidrosis	16.600759	3.409012e-02	0.0190990014	0.139098393	0.10195359	6.881518e-62
cold	16.420350	2.572208e-02	0.0127809499	0.128705756	0.08897874	1.367753e-60
oropharyngeal	15.185063	2.142891e-02	0.0108674076	0.112021944	0.07852454	4.441391e-52
abdominal	15.102233	2.993053e-02	0.0173752843	0.126577855	0.09386001	1.565400e-51
back	14.656023	2.246494e-02	0.0121010076	0.111576624	0.07983711	1.232848e-48

Fig. 8. List of group 2 comments

Finally, the comment "blood" is more significantly associated with cluster 3 and is more correlated with the comments "potassium, increased, glucose, chloride and creatinine" with 49%. These different elements show that group 3 contains more people with side effects of kidney difficulties due to the presence of chemical substances in the blood. Vaccinated people who have a side effect from this list are also more likely to have other side effects. Figure9 shows group 3 containing the most similar side effect comments.

$`3`

	v.test	Mean in category	Overall mean	sd in category	Overall sd	p.value
blood	49.507592	0.0853586370	0.0427953191	0.151787157	0.115319133	0.000000e+00
normal	42.435325	0.0758247951	0.0376489184	0.162827451	0.120669964	0.000000e+00
test	40.221152	0.0609459555	0.0340098175	0.113271961	0.089829403	0.000000e+00
increased	32.501736	0.0569516824	0.0339946007	0.117320926	0.094743147	1.007721e-231
count	32.360650	0.0370057631	0.0184660906	0.105610492	0.076846221	9.826265e-230
tomogram	32.121452	0.0393846918	0.0195397269	0.114316785	0.082869145	2.212474e-226
computerised	32.073065	0.0393301569	0.0195130291	0.114338061	0.082877746	1.047184e-225
electrocardiogram	27.113962	0.0349904942	0.0178934658	0.115419911	0.084579543	6.740345e-162
x-ray	25.891140	0.0271484697	0.0138204209	0.094457022	0.069048317	8.380070e-148
pressure	23.996863	0.0274398194	0.0138020901	0.105639906	0.076229890	2.998623e-127
full	22.899528	0.0207916447	0.0104652694	0.083750320	0.060486584	4.696733e-116
imaging	21.609492	0.0206029068	0.0102522019	0.089875562	0.064248511	1.462492e-103
resonance	21.328197	0.0201291039	0.0099997329	0.089211358	0.063703900	6.215766e-101
magnetic	21.328197	0.0201291039	0.0099997329	0.089211358	0.063703900	6.215766e-101
abnormal	21.310522	0.0422563234	0.0283984594	0.101260816	0.087224784	9.067934e-101
rate	21.092420	0.0309988627	0.0177095591	0.109624087	0.084511051	9.336121e-99
chest	20.945328	0.0441839431	0.0286630499	0.118571110	0.099395619	2.069695e-97
function	19.472261	0.0181782387	0.0094007285	0.082631528	0.060463411	1.887516e-84
cell	19.459679	0.0184116303	0.0091189177	0.090137918	0.064053745	2.412909e-84
negative	18.830041	0.0262539799	0.0151895633	0.101654315	0.078816101	4.284294e-79
cardiac	18.198512	0.0205002554	0.0106190985	0.100081602	0.072829881	5.302828e-74

Fig. 9. List of group 3 comments

Looking at all these results, we see more clearly the details of the different groups and their characteristics.

6 CONCLUSION

In this article, we have classified comments related to side effects of Covid-19 vaccines and associated the characteristics of people with categories of classes of comments. An automatic classification made it possible to identify three (3) main categories of classes of comments.

In the long term, we intend to use Bayesian networks to quantify the effects of comments on individuals by class.

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