Benchmarking French regions according to their prevalence of healthcare-associated infections

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Abstract

Objective: To propose an original method of benchmarking regions based on their prevalence of healthcare-associated infections and to identify regions with unusual results.

Design: To study between-region variability with a three-level hierarchical logistic regression model and a Bayesian non-parametric method.

Setting: French 2006 national healthcare-associated infections point prevalence survey.

Participants: 336,858 patients from 2,289 healthcare facilities in 27 regions. Patients with an imported healthcare-associated infection (1% of the data, 20.7% of infected patients),

facilities with less than 5 patients and patients who had at least one missing value for the variables taken into account were excluded (5.0% of patients).

Mean Outcome Measure: Binary outcome variable indicates whether a given patient was infected.

Results: Two clusters of regions were identified; one cluster of five regions had lower adjusted prevalence than the other one of 22 regions, while no region with unusually high prevalence could be identified. Nevertheless, the degree of heterogeneity of odds ratios between facilities for facility-specific effects of use of invasive devices was more important in some regions than in others.

Conclusions: The adjusted regional prevalence of healthcare-associated infections can serve as an adequate benchmark to identify regions with concerning results. Although no outlier regions were identified, the proposed approach could be applied to the data of the 2012 national survey to benchmark regional healthcare policies. The estimation of facility-specific effects of use of invasive devices may orient future regional action plans.

INTRODUCTION

In France, control, prevention, and surveillance of healthcare-associated infections (HAIs) are organized geographically according to local, regional, and national administrative divisions. Since the 1990s, all public and private healthcare facilities have been urged to constitute infection control committees and carry out IC programs. Currently, at the regional and inter-regional level, prevention and surveillance programs of health care facilities are developed with the support of a Centre de Coordination de la Lutte contre les infections nosocomiales (CClin) and at the national level by a steering committee coordinated by the French Ministry of Health. In addition, national HAI surveillance activities are coordinated by the Réseau d'Alerte, d'Investigation et de Surveillance des Infections Nosocomiales (RAISIN)[1].

As part of HAI prevention strategy, a national point prevalence survey of HAIs has been organized every 5 years since 1996 [2, 3]. The most recent survey with available data was conducted in 2006; it involved 2,337 health care facilities and more than 350,000 patients[3]. Compared to the incidence surveys, which could represent long periods of surveillance, point prevalence survey data may not be appropriate for inter-facility comparison because they represent a "snapshot" with limited sample size and large confidence intervals. Nevertheless, many countries still use prevalence survey data to compare groups of facilities linked by geographic proximity or with similar patient case-mixes or cooperation programs [3 - 5].

In 2009, France created Regional Health Agencies (RHA) under the Hospital, Patients, Health and Territories Act. Two levels were defined to monitor health policy in France: a national program defines actions to reduce HAI infections and then at regional level, the Regional health agencies implement policies to ensure that health care provision meets the needs of the population. The objective is to improve coordination among ambulatory, hospitals and social care sector services while controlling national health expenditures [6]. Given this governance structure, comparison of HAI prevalence at a regional level would seem to be a relevant

approach. Aggregated data, which avoid problems of limited sample size could permit regional level comparisons and identification of outlier regions, which could undergo reappraisal of their prevention strategies.

However, before using HAI prevalence as a basis for inter-regional comparisons of the quality of infection control, the measurement should be adjusted for patients' characteristics and exposure to invasive devices [7, 8] and inter-facility as well as inter-regional prevalence heterogeneity resulting from sample size heterogeneity which may bias comparisons at the regional level. In this paper, a three-level hierarchical logistic regression model was implemented with a Bayesian non-parametric method to assess between-region heterogeneity. The objective was to propose an original method of benchmarking regions according to their prevalence of healthcare-associated infections and to identify outlier regions.

METHODS

Data sources

Data were obtained from the 2006 national PPS database; they included information on 358,353 patients from 2,337 health care facilities. The participating facilities including regional hospitals, general hospitals, university hospitals, local hospitals and medicine-surgery and obstetrics clinics represented 83.3% of the HCFs and 93.6% of the inpatient beds in France. On a selected day in June, the 2006 national HAI point prevalence survey used a standardized protocol[3] prepared by the French HAI surveillance network. Data on all patients hospitalized for more than 24 hours were entered into the database by each participating facility and aggregated and anonymized at regional and national levels[9]. For each patient, the health care facility size, type and status were noted, along with the specialty of the receiving facility, the patient's characteristics, invasive device exposure and surgical procedure exposure. For those who were reported to have an infection, the location of the infection(s),

the origin (imported or acquired in the current facility), the date of diagnosis and the micro-organism(s) identified were documented.

Definition of Variables

An HAI was defined as an infection acquired during hospital care which was not present or incubating at the time of admission. The specific anatomical site definitions for HAI were standardized and adapted [9, 10] from both the definitions of the Centers for Disease Control and Prevention [11] (CDC) for acute care and the definitions of Mc Geer for long-term facilities[12].

A binary outcome variable was indicated whether a given patient had an HAI on the day of the survey.

Explanatory variables included in the current analysis were classified into patient characteristics and invasive device exposure. Patient characteristics included sex, age, ward (medicine, surgery, gynecology, intensive care, rehabilitation, long-term care, cancer, and psychiatry), immunodeficiency, surgical procedure within the past 30 days, and McCabe score. The McCabe score is a three-group classification that defines the severity of a patient's underlying medical conditions as nonfatal (score 1), ultimately fatal (in about five years, score 2), or rapidly fatal (in about one year, score 3)[13]. It was specified in the model as an ordinal variable. Invasive devices included central venous or peripheral catheters (nominal variable with three levels: no catheter, peripheral catheter, and central venous catheter), urinary catheterization, and intubation (binary variables: presence vs. absence).

Exclusion criteria

Because facility level was accounted for patients who may have acquired an HAI from a referring facility were excluded (1% of the data, 20.7% of infected patients) to avoid the ambiguity concerning the accountable facility. Patients who had at least one missing value for the variables taken into account in our analysis (sex, age, ward, immunodeficiency, surgical

procedure within the past 30 days and McCabe score) were also excluded (5.0% of patients). Since our proposed method took into account facility effect, those facilities which had less than 5 patients were also excluded (five facilities with one patient, two facilities with two patients and one facility with three patients). Thus, the analyzed dataset consisted of 2,289 health care facilities and 336,858 patients.

Data analysis and statistics

A three-level hierarchical model was implemented, with patients (level 1) nested within facilities (level 2) and facilities nested within regions (level 3). To reduce the size of the dataset, the analysis was carried out in two steps (see details in the Appendices). In the first step, a single-level logistic regression model was used to predict the risk of infection per patient according to patients' characteristics and surgery procedures. These predictions were averaged at the facility-level to generate an offset variable for each facility, which was later introduced into the facility-level dataset (step 2).

The second step involved building the three-level hierarchical regression to model the HAI prevalence using aggregate data at facility-level. The three factors not taken into account in the previous model (central venous or peripheral catheterization, urinary catheterization, and intubation) were introduced treating the facility as a random effect in order to quantify the heterogeneity of these invasive device effects between facilities. The catheterization variable was designed to be nominal since those patients who had central venous catheter in most cases had also peripheral catheter. By reducing the number of the risk factors taken into account at the facility level, aggregation of the data was simplified.

We then focused on the facility- and region-level effects on prevalence. These effects were not assumed to be constant across facilities or regions and not assumed to be completely independent because of geographic proximity and cooperative programmes among facilities.

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We assumed that facility effects were randomly drawn from a Student's- t distribution which is equivalent to an assumption of exchangeability but is more flexible than the normal distribution.

At regional level, a non-parametric distribution was used, based on a Bayesian non-parametric method [14]. We assumed that the real region effects were generated from a mixture of mass-points with each corresponding to a cluster of regions with similar prevalence. To generate this discrete distribution, we used a truncated Dirichlet process by placing a stick-breaking prior [15] over the unknown distribution F and assuming a finite number of clusters (27 in our case). Given observed data, the posterior random-effect distribution over F was obtained using Gibbs sampling[16]. After a burn-in phase of 150 000 iterations, the posterior distribution of the random effects of each region was obtained from a large number of iterations (around 100 000). At each iteration, a rank was attributed to each region according to its random-effect value. This gave the posterior distribution of the rank of each region.

RESULTS

Description of patients' and HCFs' characteristics by region

Among the 27 regions, 2,289 health care facilities, and 336,858 patients, the overall prevalence of patients with at least one HAI was 4.0%. The average number of patients per facility was 147 (min 5, max 2278). At regional level, HAI prevalence ranged from 2.1% (Corse) to 4.8% (Haute-Normandie) whereas at facility level, HAI prevalence ranged from 0 to 60% (3 HAI among 5 hospitalized patients) with a median of 4.1% (first and third quartiles: 1.4% and 6.8% respectively). The number of health care facilities per region varied from 2 in Guyane to 287 in Ile-de-France (Table I). Patients' characteristics also varied by region with the median of the regional average age being 63 years whereas the minimum was observed in region Territoires d'Outre-Mer (TOM) with an average of 40 years of age.

Effects of patients' characteristics and surgical procedure exposure

The results of the multivariate analysis at patient level illustrate the effect of patients' characteristics and exposure to surgical procedures on HAI (Table II). All the factors showed significant effects. Not surprisingly, there were large variations of the risk of HAI between patient wards with the odds of an HAI in intensive care unit about 7 times higher than those in the psychiatry unit.

Mean effect of invasive devices and heterogeneity of this effect between facilities

The use of an invasive device (catheterization or intubation) increased the odds of an HAI, but there was remarkably little inter-facility variation in the odds ratios for catherization or intubation (Table II). The medians of the OR distribution regarding the three studied factors were very similar between regions (Figure 1), yet in some regions, the heterogeneity of the ORs between facilities was more important than in other regions. For example, region Poitou-Charentes showed a median OR of 3.22 for the effect of urinary catheterization, which is really close to the overall average OR. Nevertheless, the third quartile of the distribution 3.57 was the highest of all the regions. We highlight the fact that for regions with few facilities, like Guyane (2 facilities) and TOM (5 facilities), the interpretation of ORs variability was not pertinent.

Inter-region comparison of HAI prevalence

The distribution of the regional prevalence of HAI identified clearly two clusters of regions.
The results of the model with the assumption of a mixture of two Gaussian distributions confirmed this hypothesis (Figure 2, a). One cluster included five regions had a lower

adjusted prevalence than the other cluster of 22 regions (Figure 2, b). Hence, no regional outliers with unusually high adjusted prevalence were identified.

Furthermore, the ranking based on non-adjusted prevalence values appeared to be significantly different from the one obtained with adjusted values (Figure 2, b). For instance, based on the raw prevalence, Aquitaine was ranked sixth while after adjustment it became the first. We also noted that the adjusted ranks were given with very wide credible intervals (CI), which indicates a tremendous variation in rank estimations.

DISCUSSION

Within the context of a standardized national HAI surveillance system, inter-facility and inter-region comparisons of HAI prevalence may help to improve coordination among health care services and to define strategies for infection control at regional level [3-5].

The simplest way to make such comparisons is a direct analysis of the distribution of HAI prevalence [17]. Some other approaches like control charts or the Standardized Infection Ratio are also widely used to monitor and compare quality between healthcare settings. However, most of these methods are either not risk-adjusted or performed poorly with small sample sizes and numerous risk factors [18]. The use of a multi-level regression model is considered more informative, as it permitted us to take into account inter-regional variability in the number of facilities among regions and the numbers of patients in facilities, as well as patient-level factors. In this way, not only the inherent multilevel structure of the dataset are considered, but with a proper adjustment of the prevalence, the regional and facility effect can be identified seamlessly and the effect of invasive device which varies at facility-level can be studied more efficiently without too much misleading noises. When it comes to prediction, the uncertainty may therefore be more accurately assessed.

In modelling correlated data, random effects are routinely assumed to be normally distributed (e.g., the use of league tables and hierarchical models to compare education or healthcare

providers[19, 20]). This assumption or normality presupposes that all the regions draw from the same population. However, the variability between regions may be wider than the variability allowed by a Gaussian model. Furthermore, assuming a normal distribution of the random effects tends to involve an excessive regression of the extreme values towards the overall mean[14]. This can lead to spurious interpretations. For example, an improved ranking could simply reflect the shrinkage effect related to adjustment to reflect the normal distribution.

To avoid this, our analysis was based on a Bayesian non-parametric approach[14] employing a truncated Dirichlet process to model the regional adjusted prevalence with a less restrictive random-effect distribution than the Gaussian one[21, 22]. As with the Gaussian assumption, this approach protects against extreme estimates of HAI prevalence in regions with few facilities but also against excessive regression to the mean which allowed the identification of clusters of regions.

The heterogeneity of the facility effects was modelled using a Student's-t distribution known to be more tolerant to outliers than the normal one. Even so, the posterior distribution showed an obvious skewness, which supposes a skewed normal or Student's-t distribution[23, 24]. Due to technical limitations and as our objective was not to model inter-facility heterogeneity, the case of a skewed distribution was not considered.

Nevertheless, the ranking of the regions according to their adjusted prevalence should be interpreted with caution. With a given dataset, two different models can generate two different rankings and both of them may fit the data equally well[19]. An over-interpretation of a set of rankings with wide confidence intervals can thus easily lead to unfairness. This is why we believe that it is more appropriate to keep, as main result, the existence of two clusters of regions that, according to our analysis, were clearly separated. Within each cluster, the median ranks of regions were very similar, which appears to be an inevitable consequence of attempting to rank units with similar performance.

The difference between these two clusters could be explained by different regional policies of healthcare, changes in regional surveillance programmes, or some other regional difference. Although a relatively high or increased HAI prevalence may suggest a potential problem in the IC programme, and vice versa[25], the interpretation of our results is not that simple[26].

First, although great efforts were made to ensure that all data were collected in a standardized way by trained and dedicated personnel, we cannot exclude the existence of methodological variations during the implementation of the protocol in some regions, particularly regarding HAI case finding and recording, which may have resulted in a lower PPS in some regions. Furthermore, there are still unknown characteristics at facility and at patient level that could partially explain the differences in HAI prevalence which were not taken into account in this study (e.g., differences in patient acceptance policies between facilities, types of surgical interventions, patients' comorbidities). Thus, saying that risk-adjusted differences in outcomes can be entirely attributed to the level of healthcare quality would not be true.

It is noteworthy that the French north-south gradient, frequently identified in descriptive studies of various health indicators (cancer, cardiovascular disease)[27] was found again in this cluster identification (Figure 2, c). This suggests that the level of individual morbidity considered here (i.e., the adjustment on only McCabe score) is probably not sufficient. The 2012 national point-prevalence survey is ongoing in France and in Europe, based partly on the 2006 French protocol. Improvements concerning the comorbidities were made in the new 2012 French protocol by adding information of cancer status[28, 29].

Furthermore, the obtained results may guide future action plans. For instance, in several regions such as Lorraine and Picardie, the effects of exposure to invasive devices were very similar between facilities suggesting certain homogeneity in care practices, whereas in other regions the heterogeneity of these effects was highlighted (Poitou-Charentes for urinary catheterization). This suggests a need for regional interventions to reduce the effect of

invasive devices in some healthcare facilities. Our proposed approach could as well be applied to the data of the 2012 national survey (data available from 2013) to benchmark healthcare facilities and regional healthcare policies according to their quality of care and to evaluate the impact of regional infection control programs.

CONCLUSION

The present study illustrates use of a three-level hierarchical logistic regression model with a Bayesian non-parametric method to model between-region heterogeneity. In the context of the national French HAI prevalence survey, two clusters of regions regarding HAI prevalence were identified. This type of method could be more applied for benchmarking regional healthcare policies according to their quality of care and the estimation of facility-specific effects of invasive devices may orient future regional action plans.

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Table I - Description of the patients' characteristics at regional level and of their heterogeneity between regions - French national HAI PPS, 2006.

Characteristic	Median	Min	Max
Total No. of patients	10335 (Bourgogne)	155 (Guyane)	19,795 (Ile-de-France)
Total No. of HCFs	65 (Picardie)	2 (Guyane)	287 (Ile-de-France)
Average age (year)	63 (Basse-Normandie)	39 (TOM)	68 (Limousin)
Male sex	43.7% (Rhône-Alpes)	39.7% (Alsace)	49.6% (Martinique)
Immunodeficiency	9.1% (Lorraine)	6.0% (Reunion)	12.5% (Ile-de-France)
Surgery	20.9% (Alsace)	13.9% (Guadeloupe)	24.5% (TOM)
Intubation	1.6% (Franche-Comté)	0 (Guyane)	3.8% (TOM)
Central venous catheterization	4.2% (Midi-Pyrénées)	0.7% (Guyane)	6.9% (TOM)
Peripheral arterial catheterization	18.4% (Bretagne)	11.6% (Guadeloupe)	31.0% (TOM)
Urinary catheterization	9.1% (PACA)	5.3% (Guadeloupe)	12.6% (TOM)
McCabe Score			
1	68.6% (Champagne-Ardenne)	60.7% (Guyane)	80.8% (TOM)
2	22.7% (Champagne-Ardenne)	12.8% (TOM)	35.5% (Guyane)
3	7.8% (Bourgogne)	3.9% (Guyane)	10.3% (Corse)
Hospitalisation unit			
Medicine	24.6% (Poitou-Charentes)	18.6% (Franche-Comté)	41.9% (Guyane)
Surgery	16.5% (Limousin)	13.5% (Guadeloupe)	20.7% (TOM)
Gynecology	6.0% (Champagne-Ardenne)	3.8% (Corse)	20.7% (Guyane)
Intensive care	1.5% (Limousin)	0 (Guyane)	4.2% (TOM)

Rehabilitation	17.4% (Alsace)	0 (Guyane)	25.5% (PACA)
Long-term care	18.6% (Haute-Normandie)	3.6% (Réunion)	26.8% (Limousin)
Cancer	1.6% (Bretagne)	0 (Guyane)	2.8% (Réunion)
Psychiatry	13.7% (Pays de la Loire)	0 (Guyane)	22.8% (Corse)

Table II – ([a]) Adjusted odds ratios of healthcare associated infection for patients'
characteristics and surgery procedure exposure, estimated by a single-level multiple logistic
regression model; ([b]) Estimation of the mean adjusted Odds Ratios of health-care associated
infection and of their heterogeneity between facilities, for the factors relative to invasive
device exposure. Results of the three-level logistic regression model- French national HAI
PPS, 2006.

Risk factors	Mean effect		Inter-facility variation	
	OR	95% CI	25th percentile	75th percentile
Age [a] (per five-year increment)	1.04	1.04 - 1.05	-	-
Male vs. Female [a]	1.12	1.08 - 1.17	-	-
McCabe Score [a]			-	-
1	1.00	-	-	-
2	1.87	1.82 - 1.92	-	-
3	3.50	3.31 – 3.69	-	-
Immunodeficiency [a]	1.34	1.27 - 1.41	-	-
Hospitalisation unit [a]			-	-
Psychiatry	1.00	-	-	-
Medicine	1.52	1.39 - 1.67	-	-
Gynecology	0.67	0.57 - 0.80	-	-
Intensive care	8.38	7.50 - 9.37	-	-
Rehabilitation	2.03	1.85 - 2.24	-	-
Long-term care	1.59	1.44 - 1.76	-	-
Cancer	2.29	2.01 - 2.61	-	-
Surgery	1.77	1.60 - 1.95	-	-
Surgery procedure exposure [a]	1.64	1.56 - 1.72	-	-
Intubation [b]	1.97	1.78 – 2.18	1.95	1.98
Catheterization [b]				
None	1.00			
Peripheral or arterial	1.55	1.45 – 1.65	1.44	1.58
Central venous	3.19	2.95 – 3.45	3.11	3.22
Urinary [b]	3.22	3.05 – 3.40	3.10	3.29

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Figure1
Distribution of invasive device exposure effects as estimated by the hierarchical logistic regression model at facility level, according to each region. Panel a: peripheral or arterial catheterization. Panel b: central venous catheterization. Panel c: urinary catheterization. Panel d: intubation (French national HAI PPS, 2006).

Figure2
Panel a: Distribution of the risk-adjusted prevalence of HAI in the 27 French regions. The cluster 1 included five regions: Aquitaine, Languedoc-Roussillon, Poitou-Charentes, Provence-Alpes-Côte-d'Azur, and Corse, the cluster 2 contained the other 22 regions. Panel b: posterior distribution of the ranks of the regions according to their risk-adjusted prevalence, ■: rank based on the non-adjusted prevalence. Panel c: spatial distribution of the two clusters of regions with homogeneous prevalence. Result of the three-level hierarchical model using a Bayesian approach (French national HAI PPS, 2006).

APPENDICES

The first step of the implementation consisted in the generation of an offset per facility corresponding to the part of HAI prevalence explained by the characteristics of the patients and their exposure to surgical procedures. A predicted conditional probability of HAI was obtained for each patient using a regression logistic model implemented with SAS software.

$$y_i \sim Bernoulli(\rho_i) \qquad i = 1,\ldots, 336\ 858$$

$$\text{logit}(\rho_i) = Intercept + \beta_{age} \cdot age_i + \beta_{sex} \cdot sex_i + \beta_{ward} \cdot ward_i + \beta_{immuno} \cdot immunodeficiency_i$$
$$+ \beta_{McCabe} \cdot McCabe_i + \beta_{surgery} \cdot surgery_i$$

y_i was the binary outcome corresponding to the presence or absence of at least one HAI for the patient i.

ρ_i represented the risk of HAI for the patient i.

The linear predictions omitting the intercept for the patients of each facility were averaged at the facility level to generate an offset value for each facility.

$$offset_j = \sum_{i=0}^{n_i^j} \text{logit}(\rho_i) - Intercept$$

n_i^j was the number of patients in facility j.

In the second step, a three-level hierarchical logistic regression model was built. To aggregate our dataset at facility-level, we used combinations of three extrinsic risk factors. Since central venous or peripheral catheterization was the single three-level variable (all others being binary), twelve combinations of risk factors per facility were obtained. A Bayesian analysis was then used to estimate the parameters of the model.

$$Y_{ijk} \sim Bin(\rho_{ijk}, n_{ijk}) \qquad i = 1,\ldots,27, j = 1,\ldots,2289, k = 1,\ldots,12$$

$$\text{logit}(\rho_{ijk}) = u_j + \gamma_i + offset_j + \beta_{cat1_j} \cdot Cathet1_{ijk} + \beta_{cat2_j} \cdot Cathet2_{ijk}$$
$$+ \beta_{urinary_j} \cdot Urinary_{ijk} + \beta_{intub_j} \cdot Intubation_{ijk}$$

y_{ijk} was the number of patients with HAI for the combination k of the factors introduced in the model, in facility j and region i.

n_{ijk} was the total number of patients for the combination k, in facility j and region i.

ρ_{ijk} was the probability of HAI.

u_j was the log of the HAI odds for the facility j. It corresponded to the facility random effect.

γi was the random effect of the region i expressed as a log of odds ratio.

Regional random effect distribution:

At the region-level, a non parametric distribution generated by a truncated Dirichlet Process (DP), was used to model the random effect distribution F. The main idea was to consider that the studied population was a mixture of regional clusters with various characteristics which can be represented by different normal distributions to provide larger tolerance to the outliers. The DP was the prior placing over F:

$$F \sim DP(\alpha, F_0)$$

with F_0 corresponding to a baseline distribution and α to a positive real parameter which measures the concentration of F around F_0. The higher the value of α, the closer F is to F_0. We used the stick-breaking construction of the truncated DP which assumed that our dataset was generated from a finite mixture of mass-points. It consisted in drawing N values of θ from the baseline normal distribution F_0 and N-1 values of β from a beta distribution with parameters 1 and α: $\theta_k \sim \text{Normal}\left(\mu_{F_0}, \sigma^2_{F_0}\right)$, k = 1 to N; $\beta_{k-1} \sim \text{Beta}(1, \alpha)$, k-1 = 1 to N-1

The θ_k s represented the prior random effect values of the N mass-points (random effect of region cluster k) and N corresponded to the maximum number of mass-points fixed in our case at 27, the total number of regions.

The β_{k-1}s were used to obtain the prior probabilities p_k (the probability of a region belonging to the kth cluster) assigned to the mass-points as follow: for k=1 $p_1 = \beta_1$, for k= 2 to 26

$$p_k = \prod_{i=2}^{26} (1 - \beta_{i-1}) \times \beta_k \text{, for k=27 } p_{27} = 1 - \sum_{i=1}^{26} p_i \text{ to reach the probability 1.}$$

This generation can be considered as a stick-breaking prior, as we can imagine that a stick of length 1 is broken into 27 parts. At time k, a proportion β_k of the stick remaining length is broken off, leaving a length equal to $\prod_{i=1}^{k} (1 - \beta_{i-1})$. In this way, the length of the kth part broken off is p_k.

Facilities' random effect distribution:

At the facility-level, a Student's-t Distribution was used to model the random effect distribution, in order to provide a more flexible distribution than the normal one.

For practical purposes, we considered the t-distribution parameterised as a ratio $\dfrac{Z}{\sqrt{V/\upsilon}}$, where

Z is normally distributed with mean 0 and variance 1, V has a chi-square distribution with υ degrees of freedom.

For all the parameters, priors were chosen to be weak.