Scientific Research Publishing

Open Journal of Statistics, 2024, 14, 553-575
https://www.scirp.org/journal/ojs
ISSN Online: 2161-7198
ISSN Print: 2161-718X

Practical Use of the Subjective Mathematical Model of Bayes and Its External Validation in Dental Medicine & Dentistry

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How to cite this paper: Pierre, M.M., David, K.M., Fidèle, N.B., Junior, P.K., Monique, N.M., Simplot, T.M., Jean-Paul, S.I.-B., Augustin, M.M., Em, K.K., Rosti, M., Sylvain, M.M. and Wang, D. (2024) Practical Use of the Subjective Mathematical Model of Bayes and Its External Validation in Dental Medicine & Dentistry. *Open Journal of Statistics*, **14**, 553-575.
https://doi.org/10.4236/ojs.2024.145025

Received: January 30, 2024
Accepted: October 27, 2024
Published: October 30, 2024

Abstract

Objective: Our study aims to validate the subjective Bayes mathematical model using the mathematical model of logistic regression. Expert systems are being utilized increasingly in medical fields for the purposes of assisting diagnosis and treatment planning in Dentistry. Existing systems used few symptoms for dental diagnosis. In Dentistry, few symptoms are not enough for diagnosis. In this research, a conditional probability model (Bayes rule) was developed with increased number of symptoms associated with a disease for diagnosis. A test set of recurrent cases was then used to test the diagnostic capacity of the system. The generated diagnosis matched that of the human experts. The system was also tested for its capacity to handle uncommon dental diseases and the system portrayed useful potential. **Method:** The study used the Subjective Mathematical Bayes Model (SBM) approach and employed Logistic Regression Mathematical Model (LMR) techniques. The external validation of the subjective mathematical Bayes model (MSB) concerns the real

cases of 625 patients who developed alveolar osteitis (OA). We propose strategies for reproducibility and reporting standards, outlining an updated WAMBS (when to Worry and how to Avoid the Misuse of Bayesian Statistics) checklist. Finally, we outline the impact of Bayesian analysis Logistic Regression Mathematical Model (LMR) techniques and on artificial intelligence, a major goal in the next decade. **Results:** The internal validation had identified seven (7) etiological factors of OA, which will be compared to the cases of MRL, for the external validation which retained six (6) etiological factors of OA. The experts in the internal validation of the MSB had generated 40 cases of OA and a COP of (0.5), which will be compared to the MRL that collected 625 real cases of OA to produce a Cop of (0.6) in the external validation, which discriminates between healthy patients (Se) and sick patients (Sp). Compared to real cases and the logistic regression model, the Bayesian model is efficient and its validity is established.

Keywords

External Validation-MSB-MRL, Mathematical Model

1. Introduction

The external validation of the subjective mathematical Bayes model is carried out using the calculation of the different probabilities of the occurrence of alveolar osteitis, when the identified etiological factors are present.

Bayesian Statistics (Bayesian probability) continues to remain one of the most powerful things in the ignited minds of many statisticians. In several situations, it does help us solve clinical data's problem, business problems, even when there is data involved in these problems. To say the least, knowledge of statistics will allow you to work on complex data analysis problems in machine learning and data science, irrespective of the size of the data.

In the 1770s, Thomas Bayes introduced the "Bayes Theorem." Even centuries later, the importance of "Bayesian Statistics" hasn't faded away. Therefore, Mathematical Theory of Bayesian Statistics introduces the mathematical foundation of Bayesian inference which is well-known to be more accurate in many real-world problems than the maximum likelihood method. Recent research has uncovered several mathematical laws in Bayesian statistics, by which both the generalization loss and the marginal likelihood are estimated even if the posterior distribution cannot be approximated by any normal distribution [1].

Indeed, our research of the systematic literature review in Pubmed, some articles which use the MSB in dentistry for predictive analytics of the occurrence of alveolar osteitis (OA) did not provide the articles which analyze the etiopathogenesis of alveolar osteitis (OA) by the BRAINSTORMING and nominal group technique used in our Bayesian model. This is how the use of MSB in medical sciences is essential according to Behrouz K, Julien M, and Kim AN N in their study. So to

avoid making decisions in an intuitive manner in scientific recipes, medical consultations of this MSB methodology make it possible to quantify: sensitivity, specificity and odds ratio or add ratio [2] (p. 101).

In addition, according to BLATTM and Coll, the likelihood-ratio likelihood ratio describes the performance of tests as a function of the pre-test probability (QAPRI), it combines the qualities of sensitivity and specificity in a single value and represents an objective parameter of test performance. This is defined as the ratio of the probabilities of a given test result in sick patients and healthy patients. The likelihood ratio (LHR) has a great advantage: which is its multiplication with the QAPRI (post-test probability), this allows the calculation of the QAPO (post-test probability) [3] (p. 100). According to Pewsnera D *et al.*, a test that transforms the pre-test probability (QAPRI) into the post-test probability (QAPO) can be called a "Probability Transformer". The post-test probability corresponds to the positive predictive values (NPV) [4] (p. 37).

This study is carried out in hospital settings in Kinshasa, Faculty of Medicine, University of Kinshasa and other hospitals in the Democratic Republic of Congo (DRC); it follows another previous study of the internal validation of the subjective mathematical model of Bayes, which was carried out in the same hospital environments [1]. Frequentist statistics never uses or calculates the probability of the hypothesis, while Bayesian uses probabilities of data and probabilities of both hypotheses. Frequentist methods do not demand construction of a prior and depend on the probabilities of observed and unobserved data [1].

We confirm that our study and its results are original; because we did not find it in the documentation.

We therefore claim that this study is not corroborated by previous studies carried out in Oral and Maxillofacial Surgery in the Democratic Republic of Congo (DRC) and elsewhere [2] [3].

By virtue of the above, if we manage to identify the etiological factors of the occurrence of alveolar osteitis (OA), if a model for predicting the mobility of alveolar osteitis (OA) is set up and used, if consistent actions are taken, then we can minimize the number of cases of alveolar osteitis (OA) post-dental.

1.1. A Related Work

A segmentation of dental X-ray images in medical imaging using neutrosophic orthogonal matrices was proposed by Ali *et al.* [4]. In this paper, a new fuzzy clustering algorithm based on the neutrosophic orthogonal matrices for segmentation of dental X-Ray images was proposed. This algorithm transformed image data into a neutrosophic set and computes the inner products of the cutting matrix of input. Pixels are then segmented by the orthogonal principle to form clusters. The experimental validation carried out on real dental datasets of Hanoi Medical University Hospital, Vietnam showed the superiority of the proposed method against the relevant ones in terms of clustering quality. Experimental results on the real dental X-Ray image datasets showed that the proposed method outperformed the

relevant fuzzy clustering schemes. It also showed that the proposed method achieved better validity index values. Future research of this work is to be conducted on improving the method of Bayers by an idea of Innovation System for the Preventing, Diagnosis and Prognosis of Different Dental Diseases Using Bayes Network Strategy.

1.2. Diagnosis and Suggestion of Treatment Plan

A diagnosis and suggestion of treatment plan, for example, in oral cancer in Dental Medicine is presented by Khosravi *et al.* [5]. The system receives input from user was able to analyze it and reform it. It is able to diagnose oral cancer and generate appropriate treatment in using bayers strategies method. However, system lacks clinical review to ascertain correctness of result. It only acts based on user's answers and can't study the correctness of user answers. Decision support and training system for management of endodontically treated teeth already exist [6]. One of the important attributes of the system is to train users to think holistically like an expert while solving a problem and planning treatment.

2. Study Objectives and Data Base

The aim of this article is to external validation of the subjective Bayes mathematical model using the mathematical model of logistic regression. While some knowledge acquired was then stored in a knowledge base and translated into a computer-usable language with an inference engine (a reasoning structure), that uses the knowledge appropriately. The inference engine manipulates the medical dental and dentestry knowledge acquired from the dental expert to get new knowledge. The manipulation of the inference engine on the stored knowledge in the knowledge base is likened to the reasoning of the human dental expert termed diagnosis.

Steps involved in data set acquisition were:

- Choosing what knowledge is needed;
- Obtaining the knowledge from the human dental expert;
- Analyzing the obtained knowledge;
- Storing the obtained knowledge in a knowledge base.

3. Mathematical Bayes Model & Statistic

Our study used the Subjective Mathematical Bayes Model (SBM) approach and employed Logistic Regression Mathematical Model (LMR) techniques. The external validation of the subjective mathematical Bayes model (MSB) concerns the real cases of 625 patients who developed alveolar osteitis (OA) [7]. The statistical analysis of real OA cases collected in this study made it possible to evaluate the performance of the MSB at the point of discrimination (Cut Off Point = cop 0.6). This performance evaluation consisted of comparing the MSB to real cases, and to the cases of the MRL. The MSB and the MRL complement each other in their approaches from where we compare the results of the MSB and MRL for the evaluation of the performance of the MSB, it is applied to the cases of OA collected in Hospital

Centers. To compare the MSB and MRL, we construct a contingency table to test the consistency of the results when comparing the performance of the MSB in relation to the cases of OA of the MRL with 6 risk factors, we obtain the COP = 0.6.

4. The Bayesian Statistical Technique

Bayesian statistics is a particular approach to applying probability to statistical problems. It provides us with mathematical tools to update our beliefs about random events in light of seeing new data or evidence about those events.

5. Methods

5.1. External Validation of the Prediction Model

External validation is the action of testing the original prediction model in a set of new patients to determine whether the model works to a satisfactory degree. Different validation strategies, such as internal, temporal and external validation, can be distinguished, varying in levels of rigor [6].

5.2. How Do You Validate a Predictive Model?

One common task in Precision Medicine studies is to predict the values of a specific variable. More than common task in Precision Medicine studies is to predict the values of a specific variable. More than often, this variable is likely to be costly or time-consuming to acquire and one tries to develop a more or less complex model to infer the values of this variable. As previously stated, the validation of a predictive model requires: 1) divide an initial sample set into a training and validation datasets, 2) infer a model with the training dataset, 3) evaluate the quality of the model with the validation dataset by computing the aforementioned metrics.

External validation allows us to confirm that the subjective Bayes model performs well when confronted with real cases or compared to the logistic regression model (MRL) [7].

We identified 625 cases of alveolar osteitis.

Confrontation of the subjective Bayes model (MSB) with the cases of alveolar osteitis (OA) collected in the hospitals of Kinshasa. This comparison was made by calculating the parameters S_e, S_p, VPP and VPN using the following contingency tables (Table 1 and Table 2).

Table 1. Comparison of MSB with alveolar osteitis (OA) cases.

		OA CASES		Total
		+	−	
MSB	+	A (VP)	B (FP)	$a + b = a1$
	−	A (VP)	D (VN)	$c + d = b1$
	Total	$a + c = a2$		$a + b + c + d$

Commentary of the Comparison of MSB with OA Cases:

-*A* = true positive = the predicted MSB (OA+), we have (OA+);
-*B* = false positives = the predicted MSB (OA+), we have OA−;
-*C* = false negatives = the predicted MSB OA− we have (OA+);
-*D* = true negative = the MSB predicts OA− we have OA−.
In Franch
-*A* = vrai positif = le MSB prédit (OA+), nous avons (OA+);
-*B* = faux positifs = le MSB prédit (OA+), nous avons OA−;
-*C* = faux négatifs = le MSB prédit OA− nous avons (OA+);
-*D* = vrai négatif = le MSB prédit OA− nous avons OA−.

$$S_e = \frac{a}{a+c}\times 100;\quad S_p = \frac{d}{b+d}\times 100;\quad \text{VPP} = \frac{a}{a+b}\times 100;\quad \text{VPN} = \frac{d}{c+d}\times 100;$$

$$\text{VEG} = \frac{a+d}{a+b+c+d}\times 100;\quad \text{Kappa} = \frac{\text{Po}-\text{Pe}}{1-\text{Pe}}$$

Table 2. Comparison of MSB with MRL for the alveolar osteitis model.

		MRL (COP)		Total
		+	−	
MSB	+	*A* (VP)	*B* (FP)	$a + b = a1$
	−	*C* (FN)	*D* (VN)	$c + d = b1$
	Total	$a + c = a2$	$b + d = b2$	$a + b + c + d$

-positive = the predicted MSB (OA+), we have (OA+);
-*B* = false positives = the predicted MSB (OA+), we have OA−;
-*C* = false negatives = the predicted MSB OA− we have (OA+);
-*D* = true negative = the MSB predicts OA− we have OA−.

$$S_e = \frac{A}{A+C}\times 100;\quad S_p = \frac{D}{b+d}\times 100;\quad \text{VPP} = \frac{a}{a+b}\times 100;\quad \text{VPN} = \frac{d}{c+d}\times 100;$$

$$\text{VEG} = \frac{a+d}{a+b+c+d}\times 100;\quad \text{Kappa} = \frac{\text{Po}-\text{Pe}}{1-\text{Pe}}$$

5.3. Practical Use of the Subjective Model

The combinations of factors are used in practice in General Medicine and Dental Medicine & Dentistry:

1. Factors F1, F2, F3, F4, F5, F6 and F7 are present;
2. Factors F1, F2, F3, F4 are present;
3. Factors F5, F6, F7 are present;
4. Factors F2, F3, F4, F5 are present;
5. Factors F1, F6, F7 are present;
6. Factors F3, F4, F5, F6 are present;
7. Factors F1, F2, F7 are present;
8. Factors F4, F5, F6, F7 are present;
9. Factors F1, F2, F3, F7 are present;

10. Factors F1, F3, F5, F7 are present;
11. Factors F2, F4, F6, F7 are present;
12. Factors F1, F2, F3, F5 are present;
13. Factors F1, F2, F3, F6 are present;
14. Factors F1, F2, F3, F7 are present;
15. Factors F2, F3, F4, F6 are present;
16. Factors F2, F3, F4, F7 are present;
17. Factors F2, F3, F4 are present;
18. Factors F3, F4, F5, F7 are present;
19. Factors F3, F4, F5 are present;
20. Factors F4, F5, F6 are present;
21. Factors F4, F6, F7 are present;
22. Factors F1, F2, F4, F6 are present;
23. Factors F1, F3, F4, F7 are present;
24. Factors F2, F3, F5, F7 are present;
25. Factors F2, F4, F5, F7 are present;
26. Factors F3, F4, F6, F7 are present;
27. Factors F1, F2, F4, F7 are present;
28. Factors F1, F2, F4 are present;
29. Factors F1, F3, F4, F6 are present;
30. Factors F2, F3, F5, F7 are present;
31. Factors F2, F4, F6, F7 are present;
32. Factors F1, F3, F5, F7 are present;
33. Factors F1, F3, F6, F7 are present;
34. Factors F2, F4, F5, F7 are present;
35. Factors F2, F3, F6, F7 are present;
36. Factors F1, F5, F7 are present;
37. Factors F2, F5, F6, F7 are present;
38. Factors F2, F6, F7 are present;
39. Factors F3, F5, F6, F7 are present;
40. Factors F1, F2, F5, F6 are present;
41. Factors F1, F2, F5, F7 are present;
42. ect. till 88;

88. All factors are missing F1, F2, F3, F4, F5, F6, F7.

We calculate the QAPRI, the LHR, QAPO and the probability of the occurrence of OA.

5.4. External Validation of the MSB Concerns Real Cases of OA Collected in the Eight (8) Hospital Centers

We will follow the following steps:

5.4.1. Type of Study and Place of Study

(Type of study and location)

The Quantitative Cross-Sectional Study with Analytical Purposes carried out in

the eight (8) hospital centers in Kinshasa, Democratic Republic of Congo (DRC); selected for our work.

5.4.2. Study Population and Sampling

(Study population and sampling)

We used stratified sampling. The size of each sample drawn from a medical facility stratum will be weighted to the population size of the medical facility or stratum.

6. Statistical Analyzes

The results are presented in the form of absolute value, relative frequency or mean and standard deviation. Data analyses were carried out using the standard statistical package software (SPSS 23.0 IBM, Chicago 2004) [8].

Pearson's chi-square test, the Likelihood-Ratio, and the degree of freedom are used to check whether there are relationships between risk factors and the occurrence of OA or categorical variables.

6.1. The Standard Deviation (SD) Is Used to Analyze Quantitative Variables

The standard deviation is a measure of how spread out or dispersed a set of data is from its mean or average value. It is the square root of the variance of the data

Population	Sample
$\sigma = \sqrt{\frac{\Sigma(x_i-\mu)^2}{n}}$	$S = \sqrt{\frac{\Sigma(x_i-\bar{x})^2}{n-1}}$
μ - Population Average xi - Individual Population Value n - Total Number of Population	x - Sample Average x_i - Individual Population Value n - Total Number of Sample

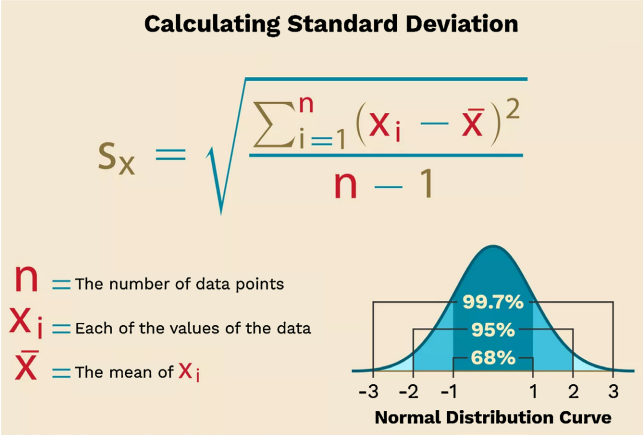

Figure 1. Calculating the Standard deviation.

set, which measures the average of the squared differences between each data point and the mean. The standard deviation is commonly used in data analysis to assess the variability of a data set and to compare different data sets. It provides a numerical measure of the degree to which individual data points deviate from the mean and allows for the identification of outliers or extreme values in the data set (**Figure 1**).

In addition, the standard deviation is used to compute confidence intervals, to test hypotheses about the data, and to make predictions about future data points. It is an important tool in statistics and is widely used in fields such as science, engineering, economics, and finance.

6.2. The Odds Ratio (OR)

The Odds Ratio (OR) is calculated for each risk factor. The odds ratio (OR) is the ratio of odds of an event in one group versus the odds of the event in the other group. An RR (or OR) of 1.0 indicates that there is no difference in risk (or odds) between the groups being compared. In addition, an odds ratio (OR) is a measure of association between an exposure and an outcome. The OR represents the odds that an outcome will occur given a particular exposure, compared to the odds of the outcome occurring in the absence of that exposure.

		OUTCOME	
		Disease (Case)	No Disease (Case)
EXPOSURE	Exposed	*a*	*b*
	Unexposed	*c*	*d*

		Event	
		Yes	Non
EXPOSURE	Yes	*a*	*b*
	No	*c*	*d*

$$\text{Odds of Exposure in Cases} = \frac{\text{Number of Cases with Exposure}}{\text{Number of Cases without Exposure}}$$

$$\text{Odds of Exposure in Controls} = \frac{\text{Number of Controls with Exposure}}{\text{Number of Controls without Exposure}}$$

$$\text{Odds Ratio} = \frac{\text{Odds of Exposure in Cases}}{\text{Odds of Exposure in Controls}} = \frac{a/c}{b/a} = \frac{a*d}{b*c}$$

$$\text{Odds Ratio} = \frac{\text{odds of the event in exposed group}}{\text{odds of the event in non-exposed group}}$$

$$\text{Odds Ratio} = \frac{a/b}{c/d} = \frac{ad}{bc}$$

$$\text{Upper 95\% CI} = e^{\left[\ln(\text{OR})+1.96\sqrt{(1/a)+(1/b)+(1/c)+(1/d)}\right]}$$

$$\text{Lower 95\% CI} = e^{\left[\ln(\text{OR})-1.96\sqrt{(1/a)+(1/b)+(1/c)+(1/d)}\right]}$$

To answer if this finding is significant, the confidence interval is calculated. The confidence interval gives an expected range for the true odds ratio for the population to fall within. If estimating the odds of lung cancer in smokers versus non-smokers of the general population based on a smaller sample, the true population odds ratio may be different than the odds ratio found in the sample. In order to calculate the confidence interval, the alpha, or our level of significance, is specified. An alpha of 0.05 means the confidence interval is 95% (1 – alpha) the true odds ratio of the overall population is within range. A 95% confidence is traditionally chosen in the medical literature (but other confidence intervals can be used). The following formula is used for a 95% confidence interval (CI).

- Upper 95% CI = e^[ln(OR) + 1.96sqrt(1/*a* + 1/*b* + 1/*c* + 1/*d*)];
- Lower 95% CI = e^[ln(OR) − 1.96sqrt(1/*a* + 1/*b* + 1/*c* + 1/*d*)].

6.2.1. Confidence Interval Interpretation

If the confidence interval for the odds ratio includes the number 1 then the calculated odds ratio would not be considered statistically significant. This can be seen from the interpretation of the odds ratio. An odds ratio greater than 1 implies that there are greater odds of the event happening in the exposed versus the non-exposed group. An odds ratio of less than 1 implies that the odds of the event happening in the exposed group are less than in the non-exposed group. An odds ratio of exactly 1 means that the odds of the event happening are the exact same in the exposed versus the non-exposed group. Thus, if the confidence interval includes 1 (e.g., [0.01, 2], [0.99, 1.01], or [0.99, 100] all include one in the confidence interval), then the expected true population odds ratio may be above or below 1, so it is uncertain whether the exposure increases or decreases the odds of the event happening with our specified level of confidence.

- The Relative Risk (RR) placed in its confidence interval made it possible to indicate the association between risk factors and the occurrence of OA.

The relative risk (RR) or risk ratio is the ratio of the probability of an outcome in an exposed group to the probability of an outcome in an unexposed group. Together with risk difference and odds ratio, relative risk measures the association between the exposure and the outcome. Relative risk is used in the statistical analysis of the data of ecological, cohort, medical and intervention studies, to estimate the strength of the association between exposures (treatments or risk factors) and outcomes. Mathematically, it is the incidence rate of the outcome in the exposed group, divided by the rate of the unexposed group. As such, it is used to compare the risk of an adverse outcome when receiving a medical treatment versus no treatment (or placebo), or for environmental risk factors. For example, in a study examining the effect of the drug apixaban on the occurrence of thromboembolism, 8.8% of placebo-treated patients experienced the disease, but only 1.7% of patients treated with the drug did, so the relative risk is .19 (1.7/8.8): patients

receiving apixaban had 19%.

6.2.2. The Disease Risk of Patients Receiving the Placebo

In this case, apixaban is a protective factor rather than a risk factor, because it reduces the risk of disease.

Assuming the causal effect between the exposure and the outcome, values of relative risk can be interpreted as follows:

- RR = 1 means that exposure does not affect the outcome;
- RR < 1 means that the risk of the outcome is decreased by the exposure, which is a "protective factor";
- RR > 1 means that the risk of the outcome is increased by the exposure, which is a "risk factor".

As always, correlation does not mean causation; the causation could be reversed, or they could both be caused by a common confounding variable. The relative risk of having cancer when in the hospital versus at home, for example, would be greater than 1, but that is because having cancer causes people to go to the hospital. Relative risk is commonly used to present the results of randomized controlled trials. This can be problematic if the relative risk is presented without the absolute measures, such as absolute risk, or risk difference. In cases where the base rate of the outcome is low, large or small values of relative risk may not translate to significant effects, and the importance of the effects to the public health can be overestimated. Equivalently, in cases where the base rate of the outcome is high, values of the relative risk close to 1 may still result in a significant effect, and their effects can be underestimated. Thus, presentation of both absolute and relative measures is recommended (**Table 3**).

Table 3. Relative risk can be estimated from a 2 × 2 contingency.

	Group	
	Intervention (I)	Control (C)
Events (E)	IE	CE
Non-events (N)	IN	CN

where *za* is the standard score for the chosen level of significance. To find the confidence interval around the RR itself, the two bounds of the above confidence interval can be exponentiated.

In regression models, the exposure is typically included as an indicator variable along with other factors that may affect risk. The relative risk is usually reported as calculated for the mean of the sample values of the explanatory variables.

6.2.3. Risk Ratio vs Odds Ratio

The degree of agreement and the Kappa statistic are used to compare the scores of Experts or investigators in order to identify agreement. The Analysis of the Data from the Subjective Bayes Model will be done in the external validation, by comparing the Bayesian model to the logistic regression model (MRL) [9] (**Figure 2**).

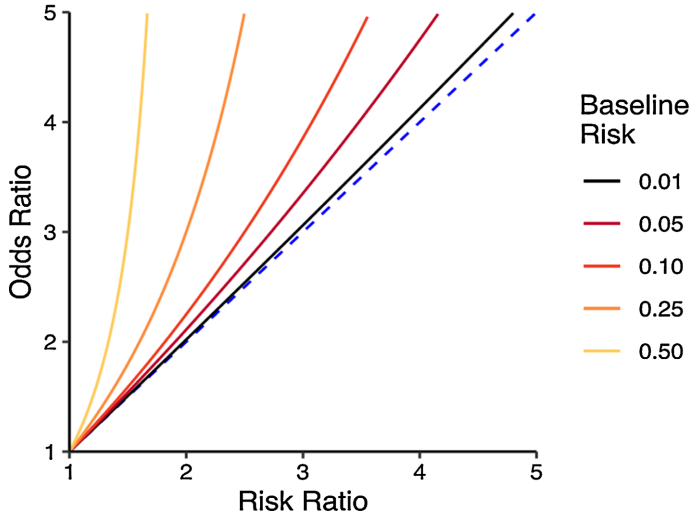

Figure 2. Risk ratio vs odds ratio.

The results were considered significant at the 5% ($P < 0.05$) uncertainty level. Logistic regression model (LRM) is used to identify independent factors associated with dependent factors.

6.2.4. Collection of Objective Data

To search for "risk factor" variables on a sample N of patients from 8 selected Medical Institutions in the City of Kinshasa, it is necessary to search for: Risk factors involved in the transition from the state of the etiological and pathological process to the stage of alveolar osteitis, MRL is indicated when phenomena result in two mutually exclusive outcomes:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + X_1\beta_1 + X_2\beta_2 + \cdots + X_n\beta_n$$

The dependent variable is the occurrence or non-occurrence of alveolar osteitis AO.

Originally ordered = O.

The coefficients are X_1, X_2, …, X_n.

Independent variables 1, 2, …, n.

P = probability.

ln = logarithm.

7. Results

7.1. Bayesian Statistics

Acquisition of Subjective and Objective Knowledge

There are two methods of acquiring knowledge:

- **The subjective and objective method**

And the roots of both of these methods go back to the classical beginning between idealist and realist philosophers. For idealists, reality exists in the minds of observers, a consensus between observers is necessary, while for realists,

reality exists independently of the observer. In a subjective approach, the emphasis is on analyzing the opinions of experts which are the statistical units, while in an objective approach, the emphasis is on direct observation which are the statistical units.

7.2. Bayesian Statistics and Traditional Statistics

7.2.1. Statistiques Bayesiennes

Bayesian statistics constitute a quantitative approach considered subjective because they study the options of experts and the consistency of their interaction. According to DEFINETTI, in this case, the order in the selection of a sample is not considered important, especially for rare, non-repetitive events. Bayesian statistics are used when a quantification process is necessary in decision making and when there is not a reliable data collection system.

7.2.2. Statistiques Traditionnelles

Traditional statistics are considered an objective approach because they study directly observable and repetitive events. In this case, it is necessary to select a sample at random. These statistics are indicated by observable and repetitive events. By their nature, the two branches of statistics have an initial bias to control:

1) A pre-experimental bias in Bayesian statistics because the experts specify their opinion on the experiment before setting up the experiment;

2) A selection bias in relation to the experimental group and the comparison group in traditional statistics.

7.3. Practical Use of the Bayes Model

Use of the MSB by calculating the different probabilities of the occurrence of OA when the factors are present [9].

7.4. Validation of MRL against MSB

The two Mathematical Models include the Subjective Bayes Model and the Logistic Regression Model which complement each other in their approaches. We must compare the results of these two approaches for the evaluation of the performance of the MSB. The MRL will be applied to OA cases collected in the eight hospital centers in Kinshasa, for our study. To confront the MSB and MRL; the contingency table is constructed to test the consistency of the results (**Table 5**).

The application of the MSB to real MRL cases made it possible to set the COP at 0.6. In this contingency table these values allow us to have the test validity parameters which are Se (69.2%), Sp (97.4%), VPP (5.6%), VPN (97.4%), VEG (50.2%) (**Table 6**).

When the results of collecting OA cases from the MRL are reported on the contingency table, the highest values of both Se, Sp, PPV, NPV and VEG are obtained at COP (0.6). This value is retained as the COP.

Table 4. Practical use of the Bayes model.

Formula: $P = \frac{Qapo}{1+Qapo}$

Cases	Risque Factors	LHR ou RV	QAPRI	QAPO	Probability	Interpretation
1	F1, F2, F3, F4, F5, F6, F7	307.03	0.21	64.4	0.98	OA present
2	F1, F2, F3, F4, F5, F7	113.71	0.21	23.8	096	OA present
3	F1, F3, F4, F6, F7	81	0.21	17	0.94	OA present
4	F2, F3, F5	7.8	0.21	1.638	0.94	OA present
5	F1, F2, F3, F4, F5, F6	9	0.21	18.9	0.94	OA present
6	F1, F2, F3, F7	60.7	0.21	127	0.92	OA present
7	F1, F3, F4, F7	54	0.21	11.34	0.91	OA present
8	F1, F3, F5, F7	54	0.21	11.34	0.91	OA present
9	F1, F3, F7	46.8	0.21	9.82	0.90	OA present
10	F2, F3, F4, F7	36	0.21	7.56	0.88	OA present
11	F3, F4, F6, F7	27	0.21	5.67	0.85	OA present
12	F1, F3, F4, F6	27	0.21	5.67	0.85	OA present
13	F2, F3, F6, F7	27	0.21	5.67	0.85	OA present
14	F1, F2, F3, F5	27	0.21	5.67	0.85	OA present
15	F3, F4, F5, F7	23.4	0.21	4.91	0.83	OA present
16	F2, F3, F5, F7	23.4	0.21	4.91	0.83	OA present
17	F3, F5, F3, F6, F7	23.4	0.21	4.91	0.83	OA present
18	F1, F3, F4, F5	23.4	0.21	4.91	0.83	OA present
19	F1, F3, F5, F6	23.4	0.21	4.91	0.83	OA present
20	F1, F2, F4, F7	23.4	0.21	4.91	0.83	OA present
21	F1, F2, F6, F7	20.25	0.21	4.25	0.80	OA present
22	F1, F4, F6, F7	20.25	0.21	4.25	0.80	OA present
23	F1, F2, F4, F5, F7	20.25	0.21	4.25	0.80	OA present
24	F1, F2, F3	20.25	0.21	4.25	0.80	OA present
25	F1, F4, F6	18	0.21	3.78	0.79	OA present
26	F2, F3, F7	18	0.21	3.78	0.79	OA present
27	F1, F2, F5, F7	18	0.21	37.8	0.79	OA present
28	F2, F3, F4, F5	17.55	0.21	3.68	0.79	OA present
29	F1, F4, F5, F7	17.55	0.21	3.68	0.79	OA present
30	F1, F5, F6, F7, F7	17.55	0.21	3.68	0.79	OA present
31	F1, F3,	17.55	0.21	3.68	0.79	OA present
32	F1, F2, F7	12	0.21	2.52	0.75	OA present

Continued

33	F1, F6, F7	13.5	0.21	2.835	0.74	OA present
34	F2, F3, F4, F6	13.5	0.21	2.835	0.73	OA present
35	F1, F4, F7	13.5	0.21	2.835	0.73	OA present
36	F1, F5, F7	11.7	0.21	2.457	0.71	OA present
37	F2, F3, F5, F6	11.7	0.21	2.45	0.71	OA present
38	F3, F7	11.7	0.21	2.45	0.71	OA present
39	F1, F2, F4, F6,	12	0.21	2.52	0.71	OA present
40	F2, F4, F6, F7	10.12	0.21	2.12	0.68	OA present
41	F2, F3, F4	10.12	0.21	2.12	0.68	OA present
42	F1, F7	10.125	0.21	2.1	0.65	OA present
43	F3, F4, F6	9	0.21	1.89	0.65	OA present
44	F2, F5, F6, F7	9	0.21	1.89	0.65	OA present
45	F4, F5, F6, F7	10.12	0.21	1.84	0.65	OA present
46	F2, F4, F5, F7	10.12	0.21	1.84	0.64	OA present
47	F1, F2, F4, F5	8.77	0.21	1.84	0.64	OA present
48	F1, F4, F5, F6	8.77	0.21	1.84	0.64	OA present
49	F1, F2, F4	8.77	0.21	1.84	0.64	OA present
50	F1, F2, F6	6.75	0.21	1.41	0.59	OA present
51	F4, F6, F7	6.75	0.21	1.41	0.59	OA present
52	F2, F6, F7	6.75	0.21	1.41	0.58	OA present
53	F1, F4, F5	6.75	0.21	1.41	0.58	OA present
54	F1, F5, F6	5.8	0.21	1.22	0.55	OA present
55	F2, F3	5.8	0.21	1.22	0.55	OA present
56	F1, F2, F5	5.8	0.21	1.26	0.55	OA present
57	F2, F5, F7	5.8	0.21	1.22	0.55	OA present
58	F4, F5, F7	5.85	0.21	1.23	0.55	OA present
59	F3, F5	5.8	0.21	1.22	0.54	OA present
60	F1, F2	5.2	0.21	1.05	0.52	OA present
61	F1, F4,	5	0.21	0.94	0.51	OA present

Table 5. Comparison of the performance of the MSB compared to the 625 cases of MRL with 6 risk factors.

	COP = 0.6															
	A	B	C	D	SUM	a1	a2	b1	b2	Pe	Po	Se	Sp	vpp	Vpn	Veg	kappa
0.1	56	265	39	265	625	51.36	0.49	0.15	0.85	8.2	0.5	58.9	87.2	17.4	87.2	51.4	1.0
0.2	56	265	39	265	625	51.36	0.49	0.15	0.85	8.2	0.5	58.9	87.2	17.4	87.2	51.4	1.0

Continued

0.3	56	265	39	265	625	51.36	0.49	0.15	0.85	8.2	0.5	58.9	87.2	17.4	87.2	51.4	1.0
0.4	56	265	39	265	625	51.36	0.49	0.15	0.85	8.2	0.5	58.9	87.2	17.4	87.2	51.4	1.0
0.5	18	303	8	296	625	51.36	51.36	51.36	51.36	51.4	51.4	51.4	51.4	51.4	87.2	51.4	1.0
0.6	1	320	1	303	625	51.36	0.49	0.04	0.96	2.6	0.5	69.2	97.4	5.6	97.4	50.2	1
0.7	1	320	1	303	625	51.36	0.49	0.00	1.00	0.6	0.5	50.0	99.7	0.3	99.7	48.6	0.4
0.8	1	320	1	303	625	51.36	0.49	0.00	1.00	0.6	0.5	50.0	99.7	0.3	99.7	48.6	0.4
0.9	1	320	1	303	625	51.36	0.49	0.00	1.00	0.6	0.5	50.0	99.7	0.3	99.7	48.6	0.4

Table 6. The selection of the Cut Off Point (COP) according to the largest value of (Se + Sp).

Criterion of discrimination or Cut Off Point (COP)	Sensitivity	Specificity	Sum= Sensitivity + Specificity
0.1	58.9	87.2	146.1
0.2	58.9	87.2	146.1
0.3	58.9	87.2	146.1
0.4	58.9	87.2	146.1
0.5	51.4	51.4	102.7
0.6	69.2	97.4	166.6
0.7	50.0	99.7	149.7
0.8	50.0	99.7	149.7
0.9	50.0	99.7	149.7

The performance of the MSB in relation to the consensus of experts (CE), to the real cases of OA and to the MRL constructed with the cases of real OA, gives the good performances in terms of sensitivities (se), specificity (Sp), value positive predictive value (PPV), negative predictive value (NPV) and overall effectiveness value (EGV). The subjective Bayers model (MSB) is used in our study on some data from internal validation (consensus of experts), and on a lot of data from real cases of external validation (MRL) for the analyses of the results. Which makes the MSB a high-performance model (Tables 7-9) (Figure 3).

Table 7. The variables of standard error, probability and t-statistic.

VARIABLES	β	Standard Error	Probability	T-Statistic	OR	(CI 95%)
(Constant)	−0.004	0.153	0.98	−0.028		
Poor Oral hygiene	0.495	0.054	0.00	9.147	16.569	(7.51:36.53)
Systemic Diseases	−0.166	0.043	0.00	−3.848	0.792	(0.55: 1.12)
Pre-existing Infections	0.263	0.134	0.04	1.969	3.234	(0.86:12.06)
Intraoperative Infection	−0.205	0.045	0.00	−4.507	0.416	(0.27:0.62)

Continued

Lack of asepsis	0.161	0.065	0.01	2.485	2.784	(1.53:5.05)
The Inexperience of the dentist	−0.037	0.046	0.42	−0.810	0.922	(0.63:1.34)
Postoperatives Infections	0.089	0.038	0.02	2.323	1.780	(1.27:2.47)

Table 8. Decision based on cut off point 0.6 on the MRL case.

	Effectives	Percentage
Présence of disease	73	11.7
Absence of disease	552	88.3
Total	625	100.0

Table 9. Indicates that we have 73 sick patients (11.7%) and 552 healthy patients (88.3%).

VARIABLES	β	Standard Error	Probability	T-Statistic	OR	(CI 95%)
(Constant)	−0.004	0.153	0.98	−0.028		
Poor Oral hygiene	0.495	0.054	0.00	9.147	16.569	(7.51:36.53)
Systemic Diseases	−0.166	0.043	0.00	−3.848	0.792	(0.55:1.12)
Pre-existing Infections	0.263	0.134	0.04	1.969	3.234	(0.86:12.06)
Intraoperative Infection	−0.205	0.045	0.00	−4.507	0.416	(0.27:0.62)
Lack of asepsis	0.161	0.065	0.01	2.485	2.784	(1.53:5.05)
The Inexperience of the dentist	−0.037	0.046	0.42	−0.810	0.922	(0.63:1.34)
Postoperatives Infections	0.089	0.038	0.02	2.323	1.780	(1.27:2.47)

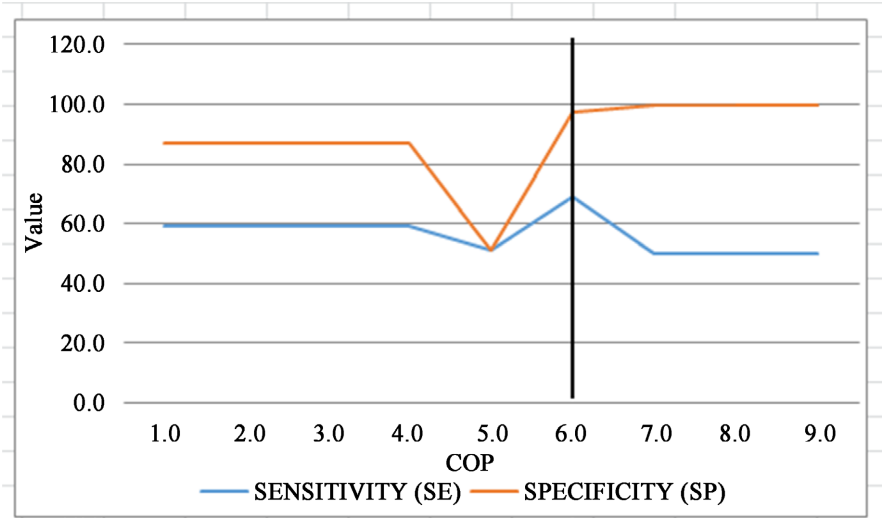

Figure 3. Determination of Cut Off Point (COP). 80.0% of Value and 6.0 of COP in Specificity is higher than the value and COP in Sensitivity. SENSITIVITY (SE) and SPECIFICITY (SP) describe the diagnostic performance of a test in a group of patients by comparing the result of the test with whether the condition of interest is actually present as indicated by a reference "golden" standard value.

7.5. Result of Logistic Regression Using the Factors Retained by the Bayesian Model

By processing the data of 625 real cases on SPSS software, the following results were obtained (Table 10).

Table 10. Logistic regression model of factors associated with alveolar osteitis.

Table Head	Effectives		
	Table column subhead	Subhead	Subhead
copy	More table copy[a]		
Table Head	Table Column Head		
	Table column subhead	Subhead	Subhead
copy	More table copy[a]		

The independent variable excluded was the inexperience of the dentist with a probability 0.42 > 0.05.

7.5.1. Estimation of the Logistic Regression Model

Ln = (ln/1-ln) = 0.227 + (0.496) poor oral hygiene + (−0.165) systemic disease + (0.263) pre-existing infection + (−0.205) intraoperative infection + (0.161) asepsis + (0.084) postoperative infection.

It appears that the factors F1: p (0.00), F2 p (0.00), F3 p (0.04), F4 p (0.00), F5 p (0.01), F7 p (0.02) have a p value < 0.05.

As mentioned at the outset, MSB and MRL achieve the same or similar results, although the two approaches are different.

7.5.2. Evaluation of Real Cases and the Logistic Regression Model (MRL) Using the Youden Index

The value of a test takes on its full meaning when we introduce the notion of prevalence which is said to be an a priori. In our study, the prevalence is 7%. For the 625 cases of OA of MRL, the Youden index is: Se (0.73.8) + Sp (87.8) − 1 = 0.62 is greater than 0.50, the test is positive, which means the partial overlap between the results of healthy patients and diseased patients. There is observable discrimination between healthy patients and sick patients.

8. Discussion

The exploitation of the results of our study is based on the contribution of Bayesian analysis in the occurrence of alveolar osteitis (OA), which identified and analyzed the multiple and potential risk factors in our context. The subjective mathematical model of Bayes (MSB) was used in this study, because in our context, we do not have a reliable system for collecting data on the occurrence of alveolar osteitis (OA). The only study carried out in Kinshasa (DRC), our context, on the etiopathogenesis of OA had identified the only factor; which does not corroborate other etiopathogenic studies on OA [6]. Predictive analysis of the

factors of the occurrence of all oral, dental, maxillofacial pathologies, etc. by the subjective mathematical model of Bayes must be exploited by all dentists, because Bayesian statistics, unlike conventional statistics, uses the intelligence of experts or investigators from which a mathematical model can be developed [6] [7]. Currently in the medical world, artificial intelligence associated with mathematics, statistics and computer science provides good performance in medical practice [6] [8] [9]. A subjective Bayesian mathematical model predicting factors for the occurrence of alveolar osteitis with six factors has high external validity as a test. The model is more valid using a multi-factor algorithm than using an algorithm with separate factors. Although these algorithms bring together a set of several factors that do not exist in the literature, it should be noted that several authors had listed several factors likely to produce OA [2] [3] [10]-[12]. Several factors for the occurrence of OA exist, but the subjective mathematical model of Bayes (MSB), only retained six factors in its external validation using the mathematical model of logistic regression (MRL), in our study carried out in hospitals in Kinshasa.

The study of conditional probabilities using the MSB is calculated with the Likelihood Ratio (LHR) to limit the difficulties in the analyses of our results. Then, our results are compared with the results of the logistic regression model (MRL) to obtain the efficient and accurate algorithms. The Bayesian approach allowed the analysis of the results of our independent factors involved in the occurrence of alveolar osteitis, as has been documented in other previous studies in Odonto-Stomatology or Dentistry for oral-maxillofacial pathologies [13]-[22]. The approach of the research study with the MRL in Odontology-Stomatology for the quantification of risk factors and the association of these factors in order to have a connection with the dependent variable (OA), have been previously carried out by some authors [2] [3] [23]-[26]. Therefore, our hope is that subsequent studies will be carried out with the Bayesian model on the occurrence of numerous oral-maxillofacial pathologies to complete the reasoning. The evaluation of our Bayesian disease prediction model is analyzed by referring to previous studies carried out at the School of Public Health of the Faculty of Medicine of the University of Kinshasa [7]. In our study, we observed that the subjective Bayes model (MSB) is a relevant solution for solving learning problems in a context of uncertainties, hypotheses and probabilities, which is that of post-alveolar osteitis. Our study is not corroborated by some previous studies which had used the MSB and that wish to introduce it in all Dental Medicine research [17]-[22]. MSB employs subjective probabilities as representations of degrees of belief and uses impersonal methods to update personal probabilities [13]-[16]. External validation of the MSB of MRL cases shows that all probabilities of 625 OA cases with six risk factors are within the Cut Off Point (COP) interval (0.1 - 0.9) and are examined between this interval to have in our MRL a COP (0.6) which discriminates between healthy patients and sick patients (Sp).

The results of sensitivity (healthy patients) and specificity (ill patients)

constitute two parameters which provide complementary and antagonistic information in our MRL [20]. Our study with the MRL gives a Youden index: 0.69 (Se) + 0.97 (Sp) − 1= 0.66 > 0.50, which means that the result is perfect, the discrimination between sick patients and healthy patients is observable [21]. The MRL retained six specific factors after evaluating the subjective Bayes model. The predictive factors retained by the MRL are poor oral hygiene, systemic diseases, intraoperative infections, preoperative infections, asepsis, post-dental extraction infections. The 7th factor which is the inexperience of the dentist was excluded by the MRL. Prevention is a priority treatment to reduce the occurrence of OA, because it allows the modifiable factors of OA to be detected in time and to intervene effectively [22]. We found in our study that neither the correct prevention, nor the correct preoperative assessment and the correct operative protocol for dental avulsions, does not eliminate OA, but helps to reduce its prevalence in our context to 7%.

Limit of the Study

Use of experts as a statistical unit.

Contribution of the Study

The development of a methodology for research in Dental Medicine based on MSB.

Advantage of the Study

The same Bayesian rules are used when we have little data or a lot of data.

Data Availability Statement

The datasets generated for this study are available on request to the corresponding author.

Ethics Statement

This study was carried out in accordance with the recommendations of Institutional Review Board of Department of Oral and Maxillofacial Surgery Dental Medicine & Dentistry, University of Kinshasa, Democratic Republic of Congo.

Authors' Contributions

MUYEMBI MUINAMINAYI Pierre, KAYEMBE MWIMBI David, NYIMI BOSHABU Fidèle, SEKELE ISSOURADI-BOURLEY Jean-Paul, MANTSHUMBA MILOLO Augustin, KALALA KAZADI EM: "Manuscript writing, Collection and assembly of data & Financial support"; MANTSHUMBA MILOLO Augustin: "Provision of study materials or patients"; MABELA Rosti, MUNYANGA MUKONGO Sylvain "Provision of study materials or patients"; DAN WANG: "Final approval of manuscript"; "All authors: accountable for all aspects of the work".

Funding

This study was sponsored by the authors.

Acknowledgements

We are grateful to Professor Dr. MUYEMBI MUINAMINAYI Pierre, Professor Dr. KAYEMBE MWIMBI David, Professor Dr. NYIMI BOSHABU Fidèle, Professor Dr. MANTSHUMBA MILOLO Augustin, Professor Dr. SEKELE ISSOURADI-BOURLEY Jean-Paul's guidance & leading this work at the University of Kinshasa in the Democratic Republic of Congo. Furthermore, we are grateful and heartfelt thanks to Professor Dr. Shu Qijin in People's Republic of China, Professor MABELA Rosti, Professor MUNYANGA MUKONGO Sylvain, DAN WANG in People's Republic of China and thankful to our colleagues' experts who were invited to manage the statistical analysis.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Muyembi, M.P., Sekele, J.P., Kashiama, B., Bobe, P., Kalala, E.M., Nyimi Bushabu, F., *et al.* (2016) Internal Validation of Subjective Bayesian Model of the Occurrence of Alveolar Osteitis Cases, Generated by Expert in Kinshasa Hospital/DRC. *Journal of Orthodontics & Endodontics*, **2**, 1-9. https://doi.org/10.21767/2469-2980.100026

[2] Barbosa, N.L., Thome, A., Maciel, C.C., Oliveria, J., *et al.* (2011) Facteurs associés aux complications de la suppression des troisièmes molaires: Une étude transversale. *Medicina Oral, Patologia Oral, Cirugia Bucal*, **16**, 376-380.

[3] Ortega, R., Loria, A. and Kelly, R. (1995) A Semiglobally Stable Output Feedback PI2D Regulator for Robot Manipulators. *IEEE Transactions on Automatic Control*, **40**, 1432-1436. https://doi.org/10.1109/9.402235

[4] Wu, J.K. (1994) Two Problems of Computer Mechanics Program System. In: *Proceedings of Finite Element Analysis and CAD*, Peking University Press, Beijing, 9-15.

[5] Pewsner, D., Bleuer, J., Bucher, H., Battaglia, M., Jüni, P. and Egger, M. (2001) Sur la voie de l'intuition? Théorème de Bayes et diagnostic en médecine générale. Partie I. *Forum Médical Suisse*, **3**, 41-45. https://doi.org/10.4414/fms.2001.04011

[6] Apaza, T., Mfiengui, N. and Ntumba, M.K. (1993) Alvéolites post-extractionnelle. A propos de 140 cas observés au Centre médico-chirurgical du Camp Kokolo à Kinshasa (RDC). *Panorama Médical*, **1**, 431-435.

[7] Grolier, J., Heresbach, D. and Josselin, J.-M. (2009) Le calcul appliqué. L'analyse coût-efficacité au service de la décision en santé publique. Presses de l'EHESP. https://www.presses.ehesp.fr/

[8] Bwira Mwokozi, E., Kamwina, K., Ngoie Bangwa, R. and Munyanga Mukongo, S. (2015) Analyse prédictive des facteurs de la survenue de l'accident vasculaire cérébrale chez les professeurs de l'Université de Kinshasa, en utilisant le modèle bayésien. *Annale de la faculté des sciences*, **1**, 31-41.

[9] Press, S.J. (2003) Subjective and Objective Bayesian Statistics: Principles, Models, and Applications. 2nd Edition, Wiley.

[10] Soureshjani, M.H. and Kimiagari, A. (2013) Calculating the Best Cut off Point Using Logistic Regression and Neural Network on Credit Scoring Problem—A Case Study of a Commercial Bank. *African Journal of Business Management*, **7**, 1414-1421.

[11] Roche, Y. and Gogly, B. (1990) Etiopathogénie de l'alvéolite sèche: Données actuelles. *Actual Odontostomatol*, **170**, 323-324.

[12] Cissokho, C.A. (1998) Le point sur les alvéolites et leur prise en charge thérapeutique: Etude prospective à propos de 68cas. Thèse en chirurgie dentaire. Dakar.

[13] Houston, J.P., Collom, J.M., Pietz, D. and Schneck, D. (2002) Alveolar Osteiyis: A Review of Its Etiology, Preventio, and Treatment Modalitites. *General Dentistry*, **50**, 457-465.

[14] Gilthorpe, M.S. and Petri, E. (2000) Introduction to Bayesian Modeling in Dental Research. *Community Dent Health*, **17**, 218-221.

[15] Bandyopadhyay, D., Reich, B.J. and Slate, E.H. (2009) Bayesian Modeling of Multivariate Spatial Binary Data with Applications to Dental Caries. *Statistics in Medicine*, **28**, 3492-3508. https://doi.org/10.1002/sim.3647

[16] Da Costa, E.P., Lee, J.Y., Rozier, R.G. and Zeldin, L. (2010) Dental Care for Pregnant Women. *The Journal of the American Dental Association*, **141**, 986-994. https://doi.org/10.14219/jada.archive.2010.0312

[17] Petrie, A., Bulman, J.S. and Osborn, J.F. (2003) Further Statistics in Dentistry Part 9: Bayesian Statistics. *British Dental Journal*, **194**, 129-134. https://doi.org/10.1038/sj.bdj.4809892

[18] Spielman, H., Schaffer, S.B., Cohen, M.G., Wu, H., Vena, D.A., Collie, D., *et al.* (2012) Restorative Outcomes for Endodontically Treated Teeth in the Practitioners Engaged in Applied Research and Learning Network. *The Journal of the American Dental Association*, **143**, 746-755. https://jada.ada.org/ https://doi.org/10.14219/jada.archive.2012.0262

[19] Dietrich, T., Culler, C., Garcia, R.I. and Henshaw, M.M. (2008) Racial and Ethnic Disparities in Children's Oral Health. *The Journal of the American Dental Association*, **139**, 1507-1517. https://jada.ada.org/ https://doi.org/10.14219/jada.archive.2008.0077

[20] Diniz, M.B., Boldieri, T., Rodrigues, J.A., Santos-Pinto, L., Lussi, A. and Cordeiro, R.C.L. (2012) The Performance of Conventional and Fluorescence-Based Methods for Occlusal Caries Detection. *The Journal of the American Dental Association*, **143**, 339-350. https://jada.ada.org/ https://doi.org/10.14219/jada.archive.2012.0176

[21] Bianchi, M., Conti, R., Delbolgive, B.N., Dellerose G., Gricco, V. and Tonelli, P. (2017) Removal of Mandibular Third Molar and Periodontal Healing of Adjacent Mandibular Second Molar: A Systematic Review. *Journal of Osseointegration Periodontics and Prosthodontics*, **9**, 65.

[22] Chattopadhyay, S., Davis, R.M., Menezes, D.D., Singh, G., Acharya, R.U. and Tamura, T. (2010) Application of Bayesian Classifier for the Diagnosis of Dental Pain. *Journal of Medical Systems*, **36**, 1425-1439. https://doi.org/10.1007/s10916-010-9604-y

[23] Afroughi, S., Faghihzadeh, S., Khaledi, M.J., Motlagh, M.G. and Hajizadeh, E. (2011) Analysis of Clustered Spatially Correlated Binary Data Using Autologistic Model and Bayesian Method with an Application to Dental Caries of 3-5-Year-Old Children. *Journal of Applied Statistics*, **38**, 2763-2774. https://doi.org/10.1080/02664763.2011.570315

[24] Anands, S.C. Singh, V., Goel, M., Verma, A. and Rai, B. (2005) Dry Socket, an Apriasal and Surgical Management. *The Internet Journal of Dental Science*, **4**, 45.

[25] Torres-Lagares, D., Gutierrez-Perez, J.L., Hita-Iglesias, P., Magallanes-Abad, N., Flores-Ruiz, R., Basallote-Garcia, M., *et al.* (2010) Randomized, Double-Blind Study of Effectiveness of Intra-Alveolar Application of Chlorhexidine Gel in Reducing Incidence of Alveolar Osteitis and Bleeding Complications in Mandibular Third Molar Surgery in Patients with Bleeding Disorders. *Journal of Oral and Maxillofacial Surgery*, **68**, 1322-1326. https://doi.org/10.1016/j.joms.2009.08.022

[26] Malik, A.S., Boyko, O., Atkar, N. and Young, W.F. (2001) A Comparative Study of MR Imaging Profile of Titanium Pedicle Screws. *Acta Radiologica*, **42**, 291-293. https://doi.org/10.1080/028418501127346846

Abbreviation

OA	Alveolar Osteitis
COP	Cut Off Point
MSB	Subjective Bayes Model
LHR	Likelihood Ratio
MRL	Logistic Regression Model
KPS	Karnofsky Performance Status
PFS	Progression Free Survival
PD	Progression Disease
LN	Lymph Node
SD	Stable Disease
PR	Partial Response
LAR	long-Acting Release