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ORIGINAL ARTICLE

Bayesian analysis of employee suggestions in a food company

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Abstract The search for competitive advantages for organizations has been made very complex by technological advancement and the ease of reproduction of resources, such as projects, products, and processes. Even new ideas are likely to be copies. However, the process of generation and conversion of improvements in productive activity is highly complex and little is known about it by firms. Understanding this process may add competitive benefits to any organization. In this paper, we present statistical modeling for data related to the counting of suggestions made by employees at a food company and its viability for improving productivity at the company. This counting, carried out in the years from 2008 through 2011, was performed and encouraged by the company's managers in order to achieve a general improvement in productivity. Poisson and binomial regression models were considered in analyzing the data under the statistical Bayesian framework. It was shown that the generation of ideas has a significant relationship to the hierarchical position of the employee, his schooling, how long he has been at the company being studied, his age, and training, but these factors do not show significant effects related to the proportions of viable ideas (potential competitive advantages for the organization).

Keywords Poisson regression · Binomial regression · Bayesian analysis · Markov Chain Monte Carlo methods

1 Introduction

According to Rothwell and Lindholm [32], traditionally, the competitive advantage of organizations is developed on their economic and financial, technological, and market capacities, to the detriment of their organizational capacity. Organizational capacity is often built on the skills of their employees, which may become a competitive advantage for the company. Yet, according to these authors, the complexity of organizations usually changes to a scenario where demands for power will become more intense, requiring its new ways for decision makers to think about work.

Human capital can be a competitive advantage for an organization, because other factors such as products, processes, and services can be imitated. Some studies show that there is a relationship between talent management practices and the increasing value of companies (see [28]).

The participation of more active and autonomous workers has led to improving productivity, worker satisfaction, and innovation in many companies, such as Nissan, Kodak, among others. The removal of barriers that limit greater participation by employees in organizations can lead to an increase not only in consumer satisfaction but also operational efficiency, reduced costs, and improved product quality (see [11] and [24]).

Different studies show that some activities by human resources management directly influence results for an organization, contributing to the reduction of absenteeism and

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disciplinary actions, increased product quality, and production efficiency, besides developing innovative capacity [6, 21, 22, 40].

According to Harb et al. [19], the challenge of organizations seems to be related to the use of new business models, based on concepts of competence and performance, plus the practice of collective learning, team development, and knowledge management, among others that offer multiple opportunities for personal and professional growth to members of the organization and encourage people not only to collectively develop the skills but also to share them.

To set up an innovative managerial practice, it can be inferred that competency-based management should have as its main objective the improvement of not only professional and organizational performances but also the development of individuals in their fullness. So this power would be at the same time both an economic value for the organization and a social value for the individual.

An alternative to the alignment of these skills is employee involvement in programs to generate ideas for improving processes, translating the knowledge and experience gained.

This competence has attracted the attention of major US organizations and growing interest from small- and medium-sized businesses. Training and development programs seek to identify specific organizational capabilities and align them with improvement in human performance [32].

According to Becker and Gerhart [4], Wright and Kehoe [41], and Arthur [2], decisions involving the management of human resources have a direct influence on the performance of the organization, and firms that have such policies based on commitment achieve better results than those based on control. In this sense, Mossholder et al. [26] argue that policies that involve collaboration among employees and their promotion may lead to more interpersonal outcomes in the short term, but wider ones in the long term.

According to Saks [33] and Huselid [20], companies that wish to improve the involvement of their employees should focus on the perceptions that employees have about the support they receive from the organization. Organizational programs that are geared to the needs of their employees and that consider and demonstrate care and support can lead the workers to higher levels of engagement, contributing to lower costs, fewer rejections, higher productivity, and greater return on direct hours worked. According to Smadi [35], a policy of employee engagement implemented appropriately contributes to continuous improvement and to raising the level of competitiveness at the organization.

Although the scientific and technical literature agrees that human resources policies, when properly planned and developed, can contribute directly and significantly to improving the economic performance of the organization, there is little scientific evidence to support these beliefs [20].

Apart from this, Bosilie et al. [6] argue that the analysis of international scientific papers on the relationship between human resource management and organizational performance leads to different perceptions: while American studies point to a more direct relationship and consider human factors to be a resource, the British papers are skeptical about this and point to a broader relationship of this factor.

According to Ahmad and Schroeder [1], studies that show the relationship involving policies on the management of human factors and organizational performance are complex to develop; however, there is some empirical evidence pointing to the positive relationship of these two aspects.

Corroborating this assertion, Ubeda [39] reports several studies that deal with the correlation between organizational performance and individual performance of the workers, implying that it would be fruitful to align organizational and individuals' skills.

However, Simón [34] argues that some assumptions, such as a strong and direct relationship between human resource management and the organization's results, are not always substantiated, requiring further study, saying that there are limitations on the ability of human resources to influence organizational outcomes. Much of what has been written about the involvement of employees comes from consulting firms and literature specific to the area, where there is little empirical and theoretical research (see [33]).

Huselid [20] states that the best organizational results have been strongly linked to many actions involving the management of human resources, programs such as worker participation, rewards systems, recruitment, selection and training, compensation systems that recognize and reward workers, among others, but one of the limitations of these findings is methodological in nature, when data is collected through questionnaires.

This view is also shared by Truss [38] and Butler et al. [8], who claim that there are limitations to the conclusions that relate the practice of human resource management to organizational outcomes, largely due to the methodological aspect involved. Apart from this aspect, many of the works dealing with the production system designs generally virtually ignore the impact of human performance on the overall performance of these processes, involving the results of the recent features to the processes itself [14].

Longitudinal studies could add clarity to the issue, but they are expensive. Hence, traditional methods (surveys) have largely been used. One alternative for this problem is to rely on the databases at the organizations [6].

For this research, we used the organization's database, containing information related to human factors at an organization with regard to their participation in the process of generating ideas and their impact on the processes.

Variations in counts of these suggestions can be related to many human factors, such as length of time in the company, education, and other factors. Statistical modeling of these data can be extremely useful in discovering factors that may affect the active participation of employees (fundamental to the improvement and competitiveness of the organization).

The main goal of this article is to statistically analyze which variables affect the generation of suggestions and feasible suggestions in a company in the food sector. The covariates to be investigated in the case study are: the level of the employee's role, schooling, length of time in the company, age of the employee, and the training received by the employee.

For statistical analysis, binomial and Poisson regression models will be assumed, whose parameters are estimated under a Bayesian approach.

In this paper, under the Bayesian paradigm, we obtain the posterior summaries of interest using existing standard Markov Chain Monte Carlo (MCMC) simulation methods, such as the popular Gibbs sampling algorithm (see [17]) or the Metropolis–Hastings algorithm (see, for example, [10]).

It is important to point out that the use of Bayesian approach presents flexibility to analyze data in presence of covariates when we can not apply standard linear regression models assuming normal errors for the data in the original scale. The use of a Bayesian approach based on simulation MCMC methods gives very accurate inference results and it is becoming a good alternative to analyze industrial data. In our statistical analysis, we are considering Binomial and Poisson regression models for discrete data sets, and the use of usual classical inference methods based on maximum likelihood estimators (asymptotical methods) to get confidence intervals and hypothesis tests could not be very accurate. Another important advantage of Bayesian methods is to include opinion from an expert in the choice of prior distributions that could imply in more accurate inferences and predictions.

As presented by Miguel [25], methodologically this work could be classified as applied, objective descriptive, and with a quantitative approach. Bertrand and Fransoo define in [5] quantitative research in engineering production as that which models a problem whose variables present quantitative causal relationships. In this sense, it becomes possible to quantify the behavior of the dependent variables in a specific field, enabling the researcher to make predictions. In general, quantitative researchers use mathematical, statistical, or computational (simulation) modeling. In this paper, statistical modeling will be adopted. As research techniques, bibliographic research and intensive direct observation will be used, according to the classification by Lakatos and Marconi [23], or bibliographic and case study research, according to the classification by Gil [18].

Bayesian methods have been widely used in applied areas, such as business administration, economics, and industrial engineering. The following are some examples from the scientific base, Scielo: Quinino and Bueno Neto [31] used Bayesian methods to assess the accuracy of quality inspectors; Pongo and Bueno Neto [30] and Droguett and Mosleh [12] proposed the use of Bayesian inference to estimate the reliability of products in new product development projects; Cavalcante and Almeida [9] used multi-criteria methods with Bayesian analysis to estimate the ideal interval for preventive maintenance; Moura et al. [27] used the Bayesian methods to assess the efficiency of maintenance; Ferreira et al. [13] used the Bayesian approach for portfolio selection problems; Barossi-Filho et al. [3] used Bayesian analysis to estimate the volatility of financial series, and Freitas et al. [15] used a Bayesian approach to estimate the wear on train the wheels.

This paper is organized as follows: Section 2 presents the binomial and Poisson regression models. Section 3 presents the case study, and Section 4 performs statistical analysis of the data presented in the case study using the models defined in Section 2. Finally, Section 5 brings the discussion of the results obtained and some final considerations.

2 Statistical modeling

To analyze the count data (suggestions and feasible suggestions), we consider two types of regression model: first of all, we assume a binomial regression model to analyze the relationship between proportions of viable suggestions and the covariates X_1 (level of the employee in the company), X_2 (schooling), X_3 (length of time in the company), X_4 (employee age), and X_5 (training), and a second regression model (Poisson regression) to analyze the relationship between the number of suggestions given by each employee and the same covariates X_1, X_2, X_3, X_4, and X_5 defined for the binomial regression model.

Let Z be a random variable with a binomial distribution given by the mass probability function,

$$P(Z = z) = \binom{n}{z} p^z (1-p)^{n-z}, \tag{1}$$

where Z denotes the number of successes in n independent Bernoulli trials. In this study, consider Z_i as the number of viable suggestions among n_i suggestions given by each employee, $i = 1, \ldots, n$.

Note that the mean and the variance of the binomial distribution (1) are, respectively, equal to np and $np(1-p)$.

To relate the success probabilities p_i to the covariates X_{1i}, X_{2i}, X_{3i}, X_{4i}, and X_{5i}, we assume a logistic regression model given by

$$\log[p_i/(1-p_i)] = \alpha_0 + \alpha_1 X_{1i} + \alpha_2 X_{2i} + \alpha_3 X_{3i} + \alpha_4 X_{4i} + \alpha_5 X_{5i}. \quad (2)$$

Let us call the model defined by Eqs. 1 and 2 as "model 1."

For a second model, let Y_i be a random variable with a Poisson distribution given by the mass probability function,

$$P(Y_i = y_i) = \frac{\exp^{-\lambda_i} {\lambda_i}^{y_i}}{y_i!}, \quad (3)$$

where $y_i = 0, 1, 2, \ldots$ denotes the number of suggestions given by the ith employee, $i = 1, 2, \ldots, n$.

Note that the mean and the variance of the Poisson distribution (3) are respectively equal to λ_i.

To relate the parameter λ_i from the Poisson distribution (3) to the covariates X_{1i}, X_{2i}, X_{3i}, X_{4i}, and X_{5i}, we assume the regression model given by

$$\log(\lambda_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i}. \quad (4)$$

The formulation (4) guarantees that λ_i is positive, for $i = 1, 2, \ldots, n$. Let us denote the model defined by Eqs. 3 and 4 as "model 2."

Assuming the two regression models defined above, the likelihood function for the vector of parameters θ associated to each model is given by

$$L(\theta) = \prod_{i=1}^{n} f(data/\theta), \quad (5)$$

where $\theta = (\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5)$ for model 1 and $\theta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$ for model 2.

For a Bayesian analysis, we assume the following prior distributions for the parameters of the models:

$$\alpha_0 \sim N(0, 10), \quad \alpha_j \sim N(0, 100), \quad j = 1, 2, 3, 4, 5 \quad (6)$$

$$\beta_0 \sim N(0, 10), \quad \beta_j \sim N(0, 100), \quad j = 1, 2, 3, 4, 5, \quad (7)$$

where $N(a, {b_j}^2)$ denotes a normal distribution with mean a and variance ${b_j}^2$. Furthermore, we assume prior independence among the parameters of the models.

Combining the joint prior distribution for the vector of parameters θ (a product of normal distributions) with the likelihood function $L(\theta)$ given in Eq. 5, we get from the Bayes formula the joint posterior distribution for θ (see [7], for example).

The posterior summaries of interest are obtained using MCMC methods. A great simplification in the simulation of samples of the joint posterior distribution for θ is obtained using the freely available software *OpenBugs* [37], which only requires the specification of the distribution for the data and the prior distributions for the parameters.

3 Case study

The sense that significant process improvements could arise as the result of small ideas led a Japanese food company to create a program of innovation at its factories, called "Production Innovation Activities" (PIA). The main objective of this program is to collect and analyze the technical and economic viability of process improvement ideas, to achieve better productivity, effectiveness, and stability.

Ideas are collected from employees in receptacles placed at strategic points in the factory. First, the ideas are classified into two categories: modification (innovation) and improvement. They are then declared by the PIA to be either "viable" or "unviable." The viable ones assume the status "being studied," "postponed," "being implemented," or "completed." When an idea is completed and it has been noted that it achieved effective benefits for the company, the person who suggested it gets a reward as defined by the program.

PIA gets about 20 ideas per month. Of all the ideas that have been studied by PIA since its creation, approximately 20 % have been approved and implemented. Several variables associated with each individual selected from a sample of the company's employees have been reported: the number of suggestions sent by the employee, the number of workable suggestions, the proportion of workable suggestions, the level of the employee's role in the company, schooling, length of time in the company, age, and training received.

The data collected for 83 employees are presented in Tables 1, 2, and 3, where we have denoted n_i the number of suggestions, Z_i the number of viable suggestions, X_{1i} denotes the level of the employee's position (1 = manager; 2 = specialist (graduated); 3 = supervisor; 4 = leader; 5= analyst; 6 = operator; X_{2i} denotes schooling (1 = university graduate; 2 = technical education; 3 = high school; 4 = illiterate); X_{3i} denotes length of time in the company (years); X_{4i} denotes the employee age; and X_{5i} denotes the number of training programs received by the employee, $i = 1, \ldots, 83$.

To analyze the data in Tables 1, 2, and 3, we have used the binomial regression model (model 1) and the Poisson regression model (model 2) considering, respectively, the proportion of viable suggestions by each employee and the number of suggestions given by each employee related to the covariates X_1, X_2, X_3, X_4, and X_5.

Figure 1 presents the graphs of the proportions of viable suggestions against the covariates level of the employee in the company.

Table 1 Associated variables for each employee of the company (in decreasing order of suggestions) - part 1

n_i	Z_i	X_{1i}	X_{2i}	X_{3i}	X_{4i}	X_{5i}
80	31	6	3	6.6	30	54
75	30	4	3	6.9	32	65
50	17	3	2	6.7	31	59
48	17	6	3	6.6	30	62
42	20	3	1	6.8	33	52
40	12	6	3	6.9	35	41
36	12	6	3	5.5	31	57
36	21	6	2	6.9	34	39
30	8	6	2	5.8	25	66
26	18	6	3	2.6	32	31
25	8	6	3	6.6	28	47
24	8	6	3	6.6	25	61
23	9	6	3	4.7	27	39
21	10	6	3	6.6	37	67
19	5	2	1	5.6	51	53
18	5	6	3	6.6	33	56
17	6	2	2	6.7	40	54
17	5	6	3	5	29	49
16	3	6	3	6.6	33	54
16	5	6	3	5.9	29	45
16	8	6	2	2.1	41	39
15	5	3	2	6.9	30	53
15	6	5	3	5.7	44	53
14	7	3	1	6.9	34	64
14	7	6	3	4.4	33	43
13	2	6	3	5	32	39
11	5	6	2	4.9	25	49
9	8	5	3	5.7	42	46

From the graphs in Fig. 1, we observe that the covariates level of the employee in the company, schooling, and length of time in the company do not apparently affect the proportion of viable suggestions.

Figure 2 shows the graphs for the numbers of suggestions by each employee against the covariates level of the employee in the company, schooling, length of time in the company, employee age, and training.

From the graphs in Fig. 2, it can be observed that the covariates level of the employee in the company, schooling, and age of the employee do not apparently affect the number of suggestions.

4 Statistical data analysis

The Bayesian statistical analysis of the data set in Tables 1, 2, and 3 is made for model 1 of Section 2, for which the proportions of viable suggestions are defined by Eqs. 1 and 2, with the prior distributions for α_0 and α_j, $j = 1, \ldots, 5$ given by Eq. 2. We also assume the variance of the prior normal distribution equal to 100, for all regression parameters; that is, a large value for the variance. In this way, we have approximately noninformative priors for the regression parameters (usually, we adopt noninformative priors for the regression parameters when we do not have prior information from experts).

Using the OpenBugs software, we have first simulated a "burn-in-sample" of 5,000, discarded to eliminate the effect of the initial values in the iterative Gibbs sampling algorithm. After this burn-in-sample period, we simulated another 100,000 Gibbs samples, taking every 100th sample to have approximately uncorrelated samples, which total a final Gibbs sample size of 1,000 to be used to get Monte Carlo estimates of the posterior means for each parameter. The posterior summaries (posterior mean, posterior standard deviations, and 95 % credible intervals) are given in Table 4. Convergence of the simulation algorithm was monitored using standard graphical methods, such as the trace

Table 2 Associated variables for each employee of the company (in decreasing order of suggestions) - part 2

n_i	Z_i	X_{1i}	X_{2i}	X_{3i}	X_{4i}	X_{5i}
9	4	6	3	4.7	32	39
9	2	6	2	4.9	30	37
9	6	4	3	5.1	27	47
8	5	6	3	4	25	51
8	8	3	2	6.7	46	57
8	2	6	3	4.1	25	51
7	6	5	3	6.5	39	49
7	1	6	3	5	32	48
6	1	6	3	6.6	32	59
6	2	6	3	6.6	35	50
6	3	1	1	5.7	31	46
6	2	5	3	4	48	53
6	1	6	3	3.1	38	37
6	4	6	3	4.5	34	51
5	3	6	3	6.6	31	47
5	2	5	1	3.8	22	39
5	4	2	1	4.2	31	50
5	1	3	3	5.11	45	38
5	1	6	3	4.1	23	52
4	2	6	3	3.11	26	29
4	2	1	1	8.7	32	21
4	2	5	2	6.7	25	54
3	2	5	3	0.11	26	41
3	0	1	1	6.6	30	39
3	2	6	3	1.1	22	32
3	3	1	1	14.11	55	39
3	2	1	1	17.1	41	39
3	0	6	3	4.4	28	40

plots of the simulated samples for each parameter (see, for example, Paulino et al. [29] or Gamerman [16]).

From the results in Table 4, we conclude that the covariates level of the employee in the company, schooling, length of time in the company, employee age, and training do not affect the proportions of viable suggestions (the 95 % credible intervals for the regression parameters $\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4$, and α_5, include the 0 value).

Now, we consider model 2 of Section 2, relating the numbers of suggestions to the covariates defined by Eqs. 3 and 4, with prior distributions for β_0 and β_j, $j = 1, \ldots, 5$ given by Eq. 7. The same simulation scheme for model 1 using the OpenBugs software is presented in Table 5. It shows the posterior summaries of interest based on a final Gibbs sample size of 1,000 for each parameter of the model.

From the results in Table 5, we conclude that only the covariates length of time in the company, employee age, and training affect the number of suggestions (the 95 % credible intervals for the regression parameters β_3, β_4, and β_5 do not include the 0 value).

Observe that X_1 and X_2 do not show significative effects on the response. In fact, these variables are categorical variables and not ordinal. To have a more sensitivity model, we decided to define dummy variables for these two variables (level of employee and schooling) considering two special levels (operator and graduates) against the other levels together.

A second Bayesian analysis is now considered with a transformation of the covariates level in company and schooling to "dummy" or "indicator" variables given respectively by W_1 (level of the employee in the company) and W_2 (schooling), where W_1 is defined by the value 1 for operator and the value 0 for the other levels in the company, and W_2 is defined by the value 1 for a graduate university education and the value 0 for the other schooling levels.

In this way, we have now models like models 1 and 2 as defined above, but now with Eq. (2) replaced by

$$\log[p_i/(1-p_i)] = \alpha_0 + \alpha_1 W_{1i} + \alpha_2 W_{2i} + \alpha_3 X_{3i} + \alpha_4 X_{4i} + \alpha_5 X_{5i}. \quad (8)$$

Table 3 Associated variables for each employee of the company (in decreasing order of suggestions) - part 3

n_i	Z_i	X_{1i}	X_{2i}	X_{3i}	X_{4i}	X_{5i}
3	2	2	1	3.2	23	32
3	3	5	1	4.2	32	37
3	0	6	3	4.7	26	51
2	0	5	2	6.5	33	47
2	2	2	1	2.6	25	32
2	1	3	1	0.2	49	8
2	0	2	1	4	27	37
2	2	5	3	3.11	41	51
2	1	6	3	5.2	30	53
2	2	5	3	3.11	28	43
1	1	3	1	6.7	59	39
1	0	1	1	6.4	29	39
1	1	5	3	3.8	35	51
1	0	5	3	3.5	29	21
1	0	5	1	4.1	27	38
1	1	5	3	3.8	25	50
1	1	6	3	1.1	35	28
1	1	5	1	4.2	29	36
1	1	6	2	1.9	29	32
1	0	6	3	1.3	24	20
1	0	6	3	6.6	33	44
1	0	5	3	4	43	49
1	1	6	3	6.6	29	46
1	0	6	3	2	31	32
1	1	6	3	4	45	52
1	1	5	1	0.11	27	20
1	1	2	1	3.1	32	39

and (4) replaced by

$$\log(\lambda_i) = \beta_0 + \beta_1 W_{1i} + \beta_2 W_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i}. \quad (9)$$

Let us denote the model defined by Eqs. 1 and 8 as "model 3" and the model defined by Eqs. 3 and 9 as "model 4."

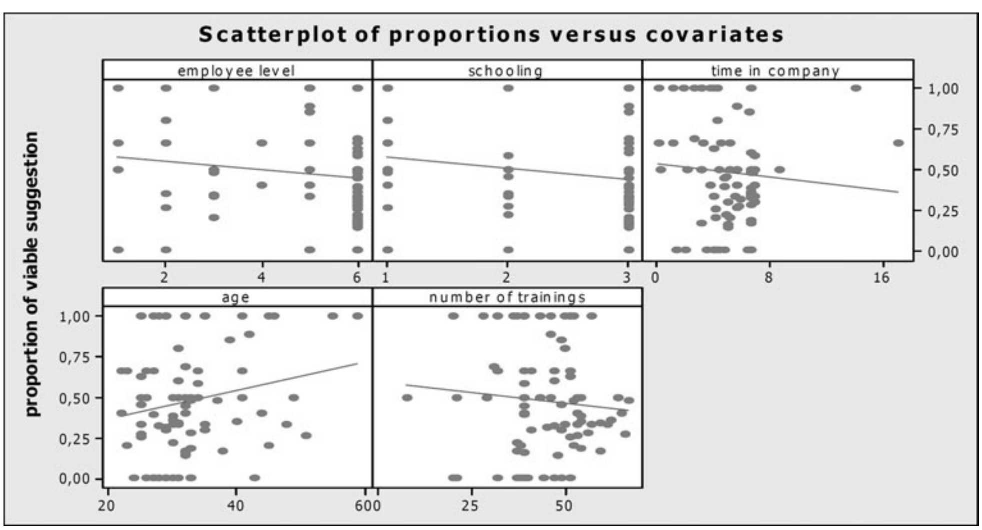

Fig. 1 Graphs of proportions of viable suggestions against covariates

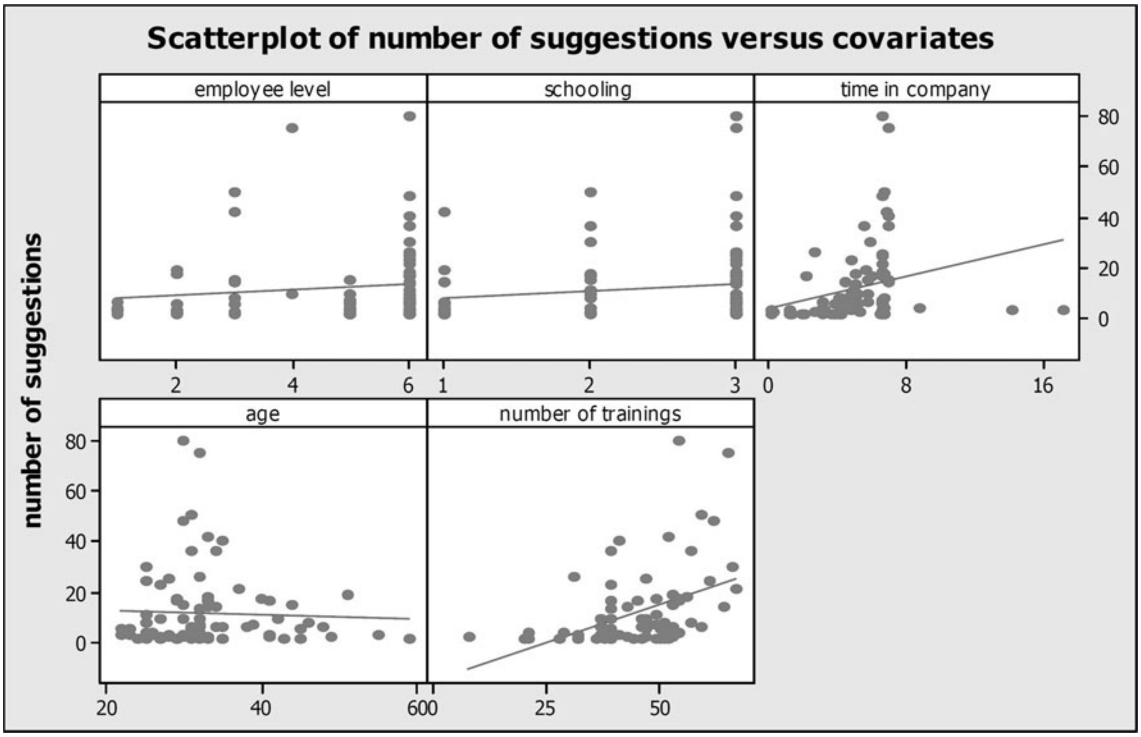

Fig. 2 Graphs of the numbers of suggestions against the covariates

Considering models 3 and 4 with Eqs. 8 and 9 in place of Eqs. 2 and 4 and the same prior distributions previously used, we have in Tables 6 and 7 the posterior summaries of interest based on 1,000 simulated Gibbs samples obtained via the OpenBugs software.

From the results in Table 6, we conclude that the covariates level of the employee in the company and training affect the proportions of viable suggestions (the 95 % credible intervals for the regression parameters α_1 and α_5 do not include the 0 value). Note that this model is more sensitive to capturing the effects of the covariates in the proportions of viable suggestions given by the employees of the company. Since the Bayesian estimate (Monte Carlo estimate of the posterior mean) for α_1 is negative, workers with a low level of education have a smaller number of viable suggestions compared with workers who have a higher level of education.

From the results in Table 7, we conclude that all covariates but level of the employee in the company affect the number of suggestions (the 95 % credible intervals for the regression parameters β_1, β_2, β_3, β_4, and β_5 do not include the 0 value).

The covariates level of the employee in the company, length of time in the company, and training positively affect the number of suggestions. We also observe that the covariates schooling and employee age negatively affect the number of suggestions. It is interesting to observe that using standard nonparametric tests, we also conclude that covariates W_1 and W_2 have significative effects on the response. In this case, the Kruskal–Wallis tests give the following p

Table 4 Posterior summaries for model 1

Parameter	Mean	Standard deviation	95 % credible interval	
α_0	0.3587	0.7071	−0.9943	1.719
α_1	−0.04358	0.07042	−0.1872	0.09475
α_2	−0.08461	0.1326	−0.3431	0.1786
α_3	−0.04623	0.0505	−0.1462	0.0552
α_4	0.0196	0.01306	−0.006635	0.04508
α_5	−0.01277	0.007502	−0.02706	0.001687

Table 5 Posterior summaries for model 2

Parameter	Mean	Standard deviation	95 % credible interval	
β_0	−0.8261	0.3018	−1.433	−0.2577
β_1	0.06884	0.03757	−0.000256	0.1422
β_2	0.1167	0.07066	−0.01834	0.259
β_3	0.1301	0.01701	0.09639	0.1634
β_4	−0.01654	0.005447	−0.0273	−0.005856
β_5	0.05131	0.003493	0.04456	0.05864

Table 6 Posterior summaries for model 3

Parameter	Mean	Standard deviation	95 % credible interval	
α_0	0.6236	0.633	−0.6575	1.843
α_1	−0.4194	0.1767	−0.7769	−0.08464
α_2	−0.01133	0.2332	−0.4651	0.4341
α_3	−0.03784	0.04915	−0.1313	0.0613
α_4	0.01235	0.01303	−0.01397	0.0373
α_5	−0.0177	0.007803	−0.03279	−0.002697

values in the comparison of the number of suggestions versus W_1 and W_2 : 0.009 and 0.008, respectively. The great advantage of our proposed model is finding the joint effects of all covariates in the response (number of suggestions) and predictions.

Figure 3 shows the graphs for the observed values (number of suggestions) for each employee and the estimated means (Bayesian estimates using model 4) against individuals. From these plots, we observe a good fit of model 4 for the data. Figure 4 shows the graphs for the observed proportions for each employee and the estimated means (Bayesian estimates using model 3) against individuals.

To decide on the best statistical model, we could use the selection Bayesian deviance information criterion (DIC) introduced by Spiegelhalter et al. [36]. The DIC is a hierarchical modeling generalization of the Akaike information criterion (AIC) and Bayesian information criterion (BIC, also known as the Schwarz criterion).

This criterion is especially useful in problems where samples of the posterior distribution for the parameters of the model have been simulated using MCMC methods.

Define the deviation as

$$D(\theta) = -2 \ln L(\theta) + C, \tag{10}$$

where θ is the vector of unknown parameters in the model, $L(\theta)$ is the likelihood function and C is a constant that does not need to be known in the comparison of models. The DIC criterion is given by

$$DIC = D(\hat{\theta}) + 2n_D, \tag{11}$$

Table 7 Posterior summaries for model 4

Parameter	Mean	Standard deviation	95 % credible interval	
β_0	−0.3237	0.2657	−0.8284	0.1941
β_1	0.2858	0.07811	0.1331	0.4315
β_2	−0.4042	0.1232	−0.646	−0.161
β_3	0.1248	0.01671	0.09191	0.1557
β_4	−0.01186	0.005352	−0.02249	−0.001661
β_5	0.04936	0.003695	0.04219	0.0567

where $D(\hat{\theta})$ is the deviation evaluated at the posterior mean $\hat{\theta} = E(\theta|data)$ and n_D is the effective number of parameters of the model given by $n_D = \bar{D} - D(\hat{\theta})$, where $\bar{D} = E(D(\theta)|data)$ is the posterior deviation measuring the quality of the data fit for the model. Smaller values of DIC indicate better models. Note that these values can be negative.

Table 8 shows the Monte Carlo estimates for DIC obtained from the 1,000 simulated Gibbs samples for each one of the four assumed models.

From the results in Table 8, we can conclude:

1. Model 3 of binomial regression is better fitted to the data when compared with model 1 since the value for DIC for model 3 is smaller.
2. Model 4 of Poisson regression is better fitted to the data when compared with model 2 since the value for DIC for model 4 is smaller.

However, the gains in DIC values comparing model 3 with model 1 are not significant since we observe a difference of only five unities between the DIC estimates. On the other hand, we observe a great difference between the DIC estimates for models 2 and 4 (a difference of 22 unities), which is an indication of a better fit for model 4 for the counting data (number of suggestions). In general, we can conclude that all covariates affect the generation of ideas in the company, but this is not true for the proportion of viable ideas. We also observe that the model with the introduction of “dummy” variables better explains the generation of new ideas in terms of level of the employee in the company and schooling level.

5 Final considerations

The adoption of the PIA program by the company studied came from the belief that greater participation by employees in organizations can lead to increased operational efficiency, reduction of costs, better product quality, and consumer satisfaction [11, 24, 26, 35]. However, the organization’s interest in identifying human factors and human resources (HR) practices that contributed to the generation of ideas and their efficacy (viable ideas) permeated the use of statistical modeling.

Specifically, this paper addressed the problem of variations in counting suggestions from employees in a company. The statistical analysis of these data, using binomial and Poisson regression models, was very useful in finding possible factors that affect the number of suggestions. The discovery of factors that act on these variations may be very important to business managers in making decisions that lead to improved business performance by ensuring their

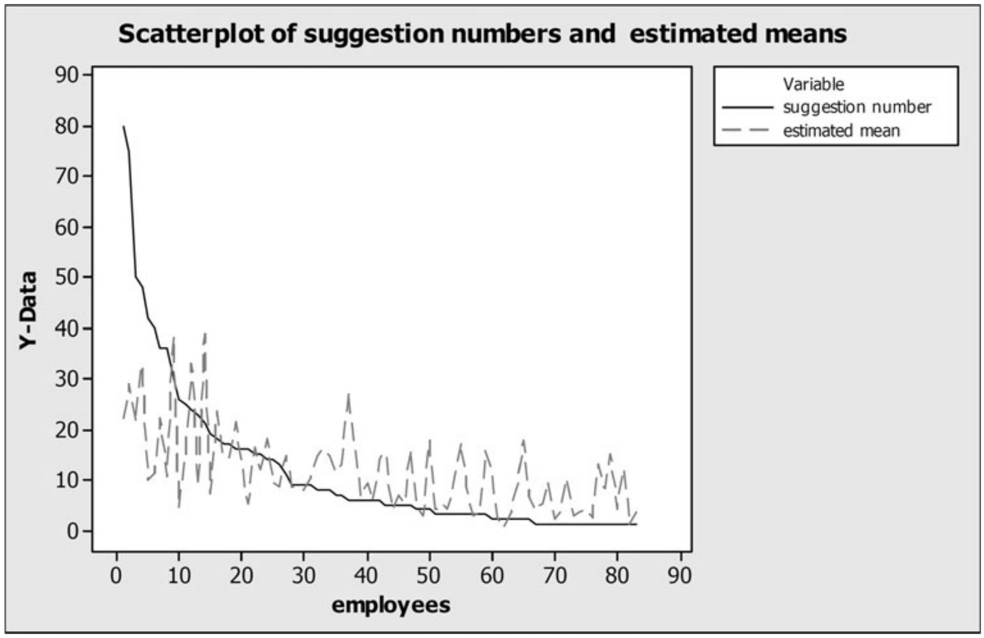

Fig. 3 Plots of the numbers of suggestions and estimated means against employees for model 4

competitive advantage (as suggested by several authors presented in the introduction). The use of the popular MCMC simulation methods for a Bayesian analysis of the proposed regression models does not require much computational cost, especially using the existing free software, OpenBugs. Such modeling can be used for other applications.

The main objective of this study was to statistically analyze which variables affect the generation of ideas and the proportion of viable ideas generated by employees at a food company. The main contribution to the area was to present empirical research since much of what is written about the involvement of employees comes from consulting firms and literature specific to the area [33].

This work has shown that the generation of ideas has a significant relationship to the hierarchical position of the employee, his schooling, his length of time in the company studies, his age, and training, but these factors do not show significant effects related to the proportions of viable ideas (potential competitive advantage for the organization). These results show a disagreement with the statements made by Huselid [20]—the best organizational results have been strongly linked to many actions involving the management of human resources.

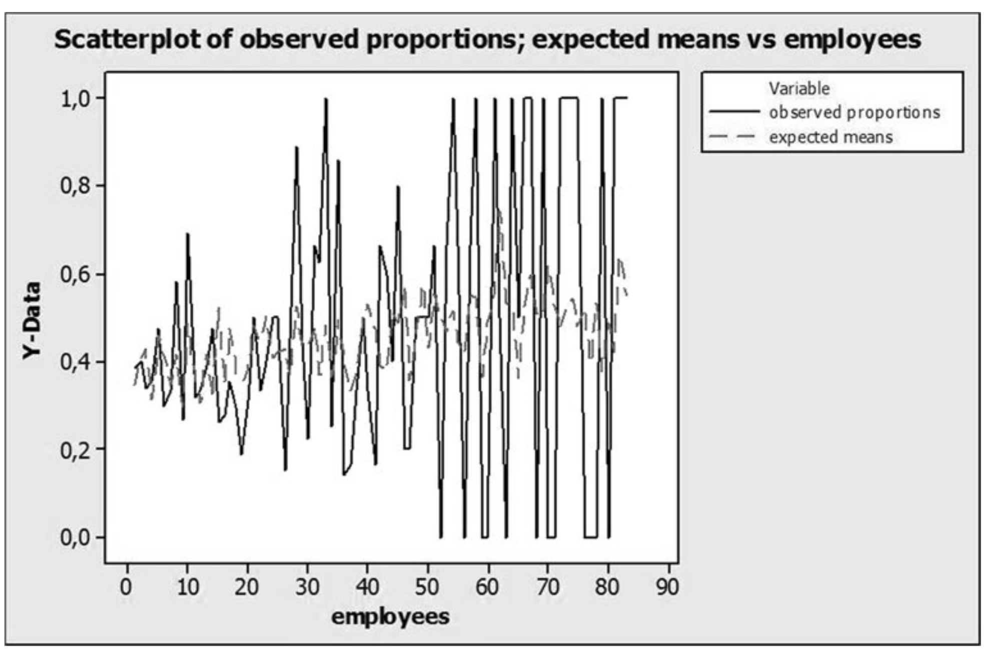

Fig. 4 Plots of the observed proportions and estimated means against employees for model 3

Table 8 Estimates for DIC

Model	DIC	
Binomial Regression	Model 1	300.0
	Model 3	295.1
Poisson Regression	Model 2	1092.0
	Model 4	1070.0

Relying on the suggestions made by Bosilie et al. [6], related to the use of organizational data in place of longitudinal studies, it is expected that this work will contribute to the statements made by Truss [38] and Butler et al. [8] about the limitations of the findings that relate the practice of managing human resources to organizational outcomes, depending on the methodological aspect involved. In this paper, the quantitative approach was not grounded on interviews (reliance on a single informant in each organization). Moreover, the statistical analysis undertaken in this work used real nonfinancial data, such as the generation of ideas and the proportion of viable ideas generated by employees.

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