PREBIOTICS BEVERAGES BASED ON CASHEW NUT ALMOND AND GRAPE JUICE: PREFERENCE ANALYSIS BY MIXED MODELS

Janaína Marques e Melo¹, Sílvia Maria de Freitas², Idemauro Antonio Rodrigues de Lara¹

¹ University of São Paulo, Luiz de Queiroz College of Agriculture, Piracicaba, São Paulo State, Brazil. E-mail: janainamem@gmail.com, idemauro@usp.br

E-mail: silvia@dema.ufc.br

ABSTRACT

In the Food and Technology Science is important to improve products and methods and this work aimed to present an analysis strategy for sensory data, using the ordinal nature of the response variables, that corresponds the hedonic scale. The data are from a study with prebiotic beverages made from cashew nut added to grape juice to evaluate its sensory characteristics and the experimental study followed a balanced incomplete block design, in which each panelist evaluated 4 of the 13 proposed beverage formulations. As statistical methods were used correspondence analysis techniques and proportional odds mixed models. better beverage formulations were selected: 8% sugar and 40% grape juice, 6% sugar and 44% grape juice and 9% sugar and 30% grape juice. It was verified that the correspondence analysis as well as the ordinal mixed models were useful for sensory data analysis, contributing to methods in the area.

Keywords: Sensory analysis; logit model; ordinal response; cumulative probabilities.

INTRODUCTION

The increasing tendency of functional benefits provided by fruits is influenced by changes in the dietary practices and consumers preferences, by the increase of population is age and by the pursuit of higher life quality (LEMOS, 2015). Therefore, food products with prebiotics are increasingly being marketed as they are healthier and help intestinal function. Another ally of good health is the cashew nut which is rich in monounsaturated and polyunsaturated fats, which lower bad cholesterol (LDL, Low Density Lipoproteins) and increases the good (HDL, High Density Lipoproteins). Moreover, the cashew apple is considered a good source of vitamin C, minerals (calcium, sodium and iron) and antioxidant substances (phenolics and carotenoids) (PEREIRA, 2013).

Demand for more research on consumer acceptability has been identified as a priority in the food industry. One area that studies the development of new beverage formulations is Food Science and Technology. It is worth mentioning that they are also responsible for evaluating products before they are released to the consumer. The evaluation of this product is carried out through sensory analysis. According to the Brazilian Association of Technical Standards (ABNT, 1993), the sensory analysis is a science used to analyze and interpret reactions to the characteristics of food and materials based on the senses of vision, smell, taste, touch, and hearing. In the evaluation of food and beverages, it is an important indicator of the acceptability of the product in the market, with the tasting experiment being properly planned by a technical team and the panelists, in turn, can be trained people or not (TEIXEIRA, 2009).

² Federal University of Ceará, Fortaleza, Ceará State, Brazil.

n general, experiments for sensory analysis are incomplete blocks design, because this area may involve many treatments (types of products or brands) with heterogeneity or limitations that restrict the size of blocks, represented by the panelists (MONTEGOMERY, 2013). Moreover, in this experimental design, each panelist does not test all products, in order not to exhaust their sensory senses, which would compromise the final analysis.

Regarding the response variable for each sensory attribute, it appears that it is on a hedonic scale, from 1 to 9, where 1 is the most unfavorable category and 9 is the most favorable category. In the discrete data literature, the variables of interest are usually ordinal polytomous (AGRESTI, 2010). In this context, although there are parametric or non-parametric methods for analyzing these data, including models for response surfaces (KHURI & CORNELL, 2018), it is recommended to respect the nature of the variable, using models for categorical data (FATORETTO et al. 2018). Also, to consider the structure of the design, random effects must be considered in the linear predictor, since the evaluator enters as a block of random nature. Therefore, the methods of mixed models are necessary (MOLENBERGHS & VERBEKE, 2006).

Thus, the present work aims to present an analysis for ordinal data, in a balanced incomplete block design, by means of the correspondence analysis and the mixed cumulative logit models with proportional odds. These methods can be applied to sensory analysis and thus contribute to product selection strategies. As motivation we have an application to a set of real data of the sensory analysis with variable ordinal polytomous response, to check the association of beverage formulation (prebiotic based on almonds of cashew nuts flavored with grape juice) and sensory factors.

MATERIAL AND METHODS

The motivational study comes from research developed in the Department of Food Science and Technology of the Federal University of Ceará, in the year 2016 (REBOUÇAS, 2016). The aim was to develop prebiotic beverages based on almond cashew nuts added to grape juice, in order to evaluate the acceptance under the sensory attributes: overall impression, aroma, thickness, sweetness and flavor, using a hedonic scale, that is composed by 9 ordinal points. Moreover, in this work, the scale was reduced to 5 points, that is, considering "5 = I liked it extremely or very much", "4 = I liked it moderately or slightly", "3 = neither liked nor disliked", "2 = disliked slightly or moderately", "1 = disliked very or extremely", to facilitate the process of fitting categorical models.

Two prebiotic substances were used for the composition of the beverages: inulin (degree of polymerization ≥10, Orafti GR) and oligofructose (2 - 8 monomers, Orafti P95). Also, commercial crystal sugar was used. To obtain the water-soluble extract, cashew nuts were used and raw. Grape juice concentrate (pH = 2.99; 15.2° Brix) was used to flavor the beverages, which was defined by means of preliminary studies.

These formulations were made by means of a 2 × 2 factorial of a central rotational compound design, with five replicates at the central point (Figure 1), in which combinations of percentages of grape juice and sugar were used, totaling 13 beverage formulations (Table 1).

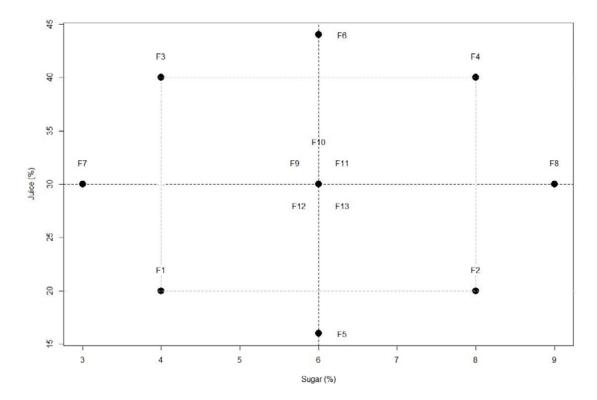


Figure 1.
Scheme 2 × 2 factorial of a central rotational compound design, with five replicates at the central point, in the study developed at the Federal University of Ceará by Rebouças (2016).

Beverage Formulation	Actual	Values	Coded Values		
	Juice(%)	Sugar (%)	Juice	Sugar	
F ₁	20	4	-1,00	-1,00	
F ₂	20	8	-1,00	+1,00	
F ₃	40	4	+1,00	-1,00	
F ₄	40	8	+1,00	+1,00	
F ₅	16	6	-1,41	0,00	
F ₆	44	6	+1,41	0,00	
F ₇	30	3	0,00	-1,41	
F ₈	30	9	0,00	+1,41	
F ₉	30	6	0,00	0,00	
F ₁₀	30	6	0,00	0,00	
F ₁₁	30	6	0,00	0,00	
F ₁₂	30	6	0,00	0,00	
F ₁₃	30	6	0,00	0,00	

Table 1.

Beverage formulations developed at Federal University of Ceará, in 2016, with grape juice and prebiotic substances, where formulations 9-13 are defined as "Central Point".

Source: Adapted from Rebouças (2016)

The sensory acceptance evaluation of the proposed formulations (F_1 to F_{13}) was performed in different sessions, in which 130 untrained participated (panelists). Samples were served sequentially monadic, following a balanced incomplete block design, in which each panelist evaluated 4 of the 13 formulations of the proposed beverages, as showed in the Figure 2.

When studying categorical data, contingency tables and association tests between variables are useful techniques for exploratory data analysis. Therefore, in this work we have used these techniques to verify the association between beverage formulations and sensory attributes, using the Chi-square test. Also, multivariate techniques to categorical data by means correspondence analysis graphics (JOHNSON &WICHERN, 2008) were applied to complete data description. These methods, although exploratory, previously identify possible associations and clusters.

To relate the formulations to the response variables (overall impression, aroma, body, sweetness, and flavor) we use models for categorical data, called cumulative

logits (AGRESTI, 2010). These models are multivariate extensions to the logistic regression model, specific to dichotomous data. In this class models, we can use the simplest structure, proportional odds, where formulation effects are constant for each category of the hedonic scale. Also, we include a random effect associated to panelist, due to design structure (incomplete blocks) as well as the subjective variability to the panelist. In this context, the mixed proportional odds model is given by

$$\eta_j = logit[P(Y \le j)] = ln \left[\frac{P(Y \le j \mid \mathbf{x}.\mathbf{z})}{1 - P(Y \le j \mid \mathbf{x}.\mathbf{z})} \right] = \boldsymbol{\alpha}_j + \boldsymbol{\beta}_j^T \mathbf{x} + b^T \mathbf{z}$$
 (1)

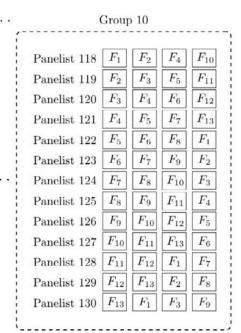
where, \mathbf{a}_j is the intercept, $\mathbf{\beta}_j = (\beta_1, \beta_2, ..., \beta_{13})^T$ is the regression parameters vector associated to beverage formulation, which vary according to each response category (j=1,2,3,4,5), and \mathbf{b} is the random effect associated with the panelist, where we supposing $\mathbf{b} \sim N(0, \sigma_b^2)$. A more parsimonious model than the cumulative logit model (eq. 1) is the so-called proportional odds model (eq. 2), which assumes proportionality of the odds ratio in each logit, as follows:

$$\eta_{j} = logit[P(Y \le j)] = ln \left[\frac{P(Y \le j \mid \mathbf{x}, \mathbf{z})}{1 - P(Y \le j \mid \mathbf{x}, \mathbf{z})} \right] = \boldsymbol{\alpha}_{j} + \boldsymbol{\beta}^{T} \mathbf{x} + \boldsymbol{b}^{T} \mathbf{z}$$
 (2)

	Gro	up 1		
Panelist 1	F_1	F_2	F_4	F_{10}
Panelist 2	F_2	F_3	F_5	F_{11}
Panelist 3	F_3	F_4	F_6	F_{12}
Panelist 4	F_4	F_5	F_7	F_{13}
Panelist 5	F_5	F_6	F_8	F_1
Panelist 6	F_6	F_7	F_9	F_2
Panelist 7	F_7	F_8	F_{10}	F_3
Panelist 8	F_8	F_9	F_{11}	F_4
Panelist 9	F_9	F_{10}	F_{12}	F_5
Panelist 10	F_{10}	F_{11}	F_{13}	$\overline{F_6}$
Panelist 11	F_{11}	F_{12}	F_1	F_7
Panelist 12	F_{12}	F_{13}	F_2	F_8
Panelist 13	F_{13}	F_1	F_3	F_9

Panelist 14	F_1	F_2	F_4	F_{10}
Panelist 15	F_2	F_3	F_5	F_{11}
Panelist 16	F_3	F_4	F_6	F_{12}
Panelist 17	F_4	F_5	F_7	F_{13}
Panelist 18	$oxed{F_5}$	F_6	F_8	F_1
Panelist 19	F_6	F_7	F_9	F_2
Panelist 20	F_7	F_8	F_{10}	F_3
Panelist 21	F_8	F_9	F_{11}	F_4
Panelist 22	F_9	F_{10}	F_{12}	F_5
Panelist 23	F_{10}	F_{11}	F_{13}	F_6
Panelist 24	F_{11}	F_{12}	F_1	F_7
Panelist 25	F_{12}	F_{13}	F_2	F_8
Panelist 26	F_{13}	F_1	F_3	F_9

Group 2



where, $\beta = (\beta_1, \beta_2, ..., \beta_{13})^T$ is the same for each response category and the other parameters are defined as in model given the eq. 1. Additional details about the cumulative logit models can be seen in Paulino and Singer (2006), Agresti (2010), and Tutz (2012).

The estimates of these parameters are obtained by the maximum likelihood theory, by means the Newton-Raphson's interactive process (AZZALINI, 2017). The computational implementation was conducted in the R software (R CORE TEAM, 2022), using the packages: ordinal (CHRISTENSEN & BROCKHOFF, 2013) and VGAM (YEE, 2019). Moreover, as the models (1 and 2) are nested the verification of the proportionality condition is done by the Likelihood Ratio Test (LRT). The statistical significance of the formulation effect as well as is done by LRT. The LRT is defined by the expression:

$$\lambda = -2\log\left(\frac{L_0}{L_1}\right)$$

where L_0 is the likelihood function under the model with less parameters, that is, restricted model, and and L_1 represents the likelihood function under unrestricted model. For decision we consider that $\Lambda \sim \chi^2_{(m,95\%)}$, where m is the degree of freedom (difference of the parameters number). After model selection and with the estimated regression parameters in the in linear predictor (η_i) , the accumulated probabilities associated with each formulation for each attribute are given by:

$$\hat{\theta}_j = \widehat{P}(Y \le j) = \frac{\exp(\widehat{\eta}_j)}{1 + \exp(\widehat{\eta}_j)}$$

Moreover, in this work, as a criterion for selecting the best formulations, we consider predictions greater than or equal to 4, $\hat{P}(Y \ge 4) = \hat{\theta}_{i=5} - \hat{\theta}_{i=3}$.

RESULTS AND DISCUSSIONS

Before applying correspondence analysis, we have verified the associations among beverage formulations (F_1 to F_{13}) and the sensory attributes (overall impression, aroma, thickness, sweetness and flavor). For this, the chi-square association test was applied to evaluate the possible dependence.

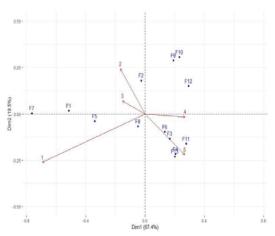
The five sensory attributes (Overall Impression, Aroma, Thickness, Sweetness and Flavor) have presented significant association with formulations (*values -p<0.05*). There is evidence that the sensory attributes and beverage formulations are dependent and we can apply the correspondence analysis. The graphics with exploratory analysis are shown in Figure 3 for all attributes.

The percentages of explained observations in two dimensions by each attributes (Overall Impression, Aroma, Thickness, Sweetness and Flavor) were: 86.9% (Figure 3a), 83.2% (Figure 3b), 80.0% (Figure 3c), 83.8% (Figure 3d) and 84.1% (Figure 3e), respectively.

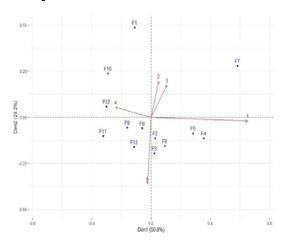
It is also observed that the beverage formulations that came closer to category 5 ("liked extremely"), for overall impression attribute were F_3 , F_4 , F_6 , F_{11} and F_{13} (Figure 1a). Considering aroma attribute, it was F_5 (Figure 1b) and for body attribute they were F_2 , F_3 , F_6 , F_8 and F_{13} (Figure 1c). Furthermore, for sweetness attribute they were F_6 , F_{11} and F_{13} (Figure 1d). Finally, the formulations F_{10} , F_{11} , F_{12} and F_{13} for flavor attribute (Figure 1e).

The proportional odds likelihood ratio test (2) results are shown in Table 2. For all sensory attributes the tests were not significant (values -p>0.05). Consequently, the mixed proportional odds models (1) were fitted considering a random panelist effect.

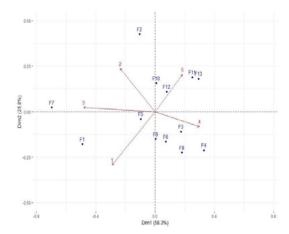
Figure 3. (a,b,c,d,e) Correspondence analysis of beverage formulation versus sensory attributes



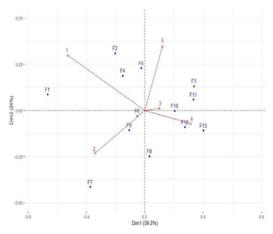
(a) Sensory attribute points cloud overall impression versus beverage formulation



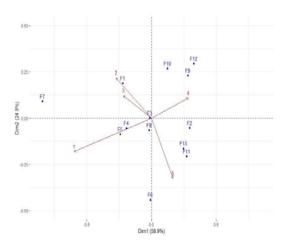
(c) Sensory attribute points cloud body versus bebeverage formulation



(e) Sensory attribute points cloud flavor versus beverage formulation



(b) Sensory attribute points cloud aroma versus beverage formulation



(d) Sensory attribute points cloud sweetness versus beverage formulation

It was verified that the standard deviation estimation of random effect was $\hat{\sigma}_b$ =2.13, with an 95% confidence interval equal to (1.75; 2.58), that does not contain zero, indicating the existence of a random effect for the model (1) with overall impression as response.

existence of a random effect for the model (1) with overall impression as response. The estimated parameters, standard errors, Z statistic test and *p-values* for this model are presented in the Table 3. We can observe that β_5 and β_7 were non-significant, indicating that

 β_1 = β_5 = β_7 , meaning that F_1 , F_5 and F_7 beverage formulations can be considered with equal effects. It is also verified that the estimates of β_4 , β_6 and β_{13} obtained the highest values (in module) showing a greater acceptance of F_4 , F_6 and F_{13} beverage formulations by the panelists, results previously indicated by the exploratory analysis (Figure 3).

The estimated probabilities for overall impression from this fitted model as well as the expected cumulative probability values for response categories 4 (liked slightly) and 5 (liked extremely) are shown in Table 4. Here we use the cumulative probability of these categories (which indicate better evaluation) as a criterion to select the best formulations, it is observed that the formulations F_4 , F_6 and F_{13} obtained the highest accumulated probabilities with 0.80, 0.77 and 0.75, respectively.

We chose not to present the results for the other attributes, but the model used is the same, that is, mixed proportional odds. Also, a similar criterion was used to select the attributes. The categories "4 = I liked it moderately or slightly" and "5 = I liked it extremely or very much", for

each attribute, indicates better formulation evaluations obtained the highest cumulative probability as following results: aroma - F_6 : 0.49, F_{12} : 0.47, F_{13} : 0.48; thickness - F_6 : 0.81, F_9 : 0.77, F_{13} : 0.78; sweetness - F_6 : 0.84, F_{11} : 0.79, F_{13} : 0.80 and flavor - F_4 : 0.85, F_6 : 0.75, F_{13} : 0.74. Due to these factors, we can observe that formulations F_6 and F_{13} are included in all attribute results. As an evaluation criterion of model (1) for overall impression, we present in Figure 4 the observed proportions and predicted probabilities, and the measures are quite close, indicating the model is satisfactory to explain the functional relationship.

Sensory Attribute	p-values
Overall Impression (OI)	0.246
Aroma (AR)	0.054
Thickness (TH)	0.067
Sweetness (SW)	0.170
Flavor (FL)	0.157

Table 2.Proportional odds test, beverage formulations versus sensory attributes.

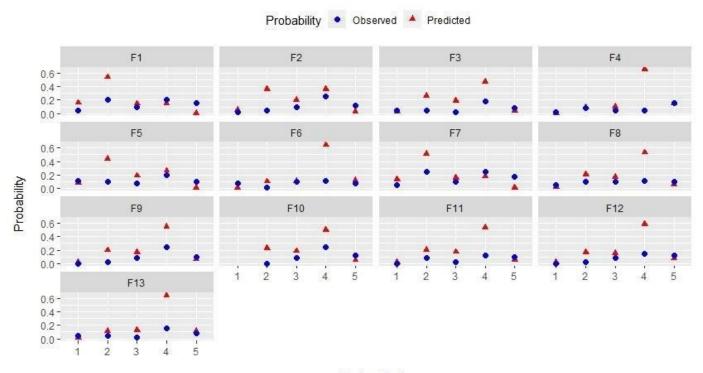
Parameter	Estimate	Standard error	z	p-values
$\alpha_{_4}$	-4.79	0.48	-10.04	<0.01
a_3	-1.65	0.41	-3.99	<0.01
a_2	-0.82	0.41	-2.02	0.04
$\alpha_{_1}$	1.67	0.41	4.03	<0.01
$oldsymbol{eta}_2$	-1.18	0.49	-2.42	0.02
$oldsymbol{eta}_3$	-1.71	0.50	-3.44	<0.01
$oldsymbol{eta}_4$	-3.02	0.52	-5.77	<0.01
$oldsymbol{eta}_5$	-0.70	0.49	-1.43	0.15
$oldsymbol{eta}_{6}$	-2.85	0.52	-5.52	<0.01
β_7	-0.19	0.50	-0.38	0.70
$oldsymbol{eta}_{8}$	-2.03	0.51	-4.01	<0.01
$oldsymbol{eta}_{9}$	-2.09	0.49	-4.23	<0.01
$oldsymbol{eta}_{ exttt{10}}$	-1.86	0.49	-3.80	<0.01
$oldsymbol{eta}_{11}$	-2.04	0.50	-4.11	<0.01
$eta_{_{12}}$	-2.31	0.50	-4.61	<0.01
$oldsymbol{eta_{13}}$	-2.76	0.52	-5.34	<0.01

Table 3.
Parameter estimates, standard errors and statistical tests for beverage formulation effects for overall impression attribute response

Table 4.Proportions of each classification of beverage formulation with sensory attribute overall impression.

Beverage	Overall Impression response category					DN 4
Formulation	1	2	3	4	5	P≥4
F ₁	0.16	0.54	0.15	0.15	0.01	0.16
F ₂	0.06	0.36	0.20	0.36	0.03	0.39
F ₃	0.03	0.26	0.19	0.47	0.04	0.52
F ₄	0.01	0.09	0.10	0.65	0.15	0.80
F_5	0.09	0.44	0.19	0.26	0.02	0.28
F ₆	0.01	0.11	0.12	0.64	0.13	0.77
F ₇	0.14	0.52	0.16	0.18	0.01	0.19
F ₈	0.02	0.21	0.18	0.53	0.06	0.59
F ₉	0.00	0.20	0.17	0.55	0.06	0.61
F ₁₀	0.00	0.00	0.19	0.50	0.05	0.55
F ₁₁	0.00	0.20	0.18	0.54	0.06	0.60
F ₁₂	0.00	0.17	0.16	0.58	0.08	0.66
F ₁₃	0.01	0.11	0.12	0.64	0.12	0.75

Figure 4.Observed and predicted proportions for overall impression attribute by the beverage formulation.



Rating Scale

CONCLUSIONS

The present work shows a statistical approach for data analysis in sensory area, with emphasis in mixed cumulative logit models with proportional odds. Also, we present the correspondence analysis as an important exploratory technique. Using these procedures, we have concluded that F₆ and F₁₃ formulations were the best evaluated in the global impression criterion and the other attributes. Although in this work the orientation was by the proportional chances model, it is worth mentioning that this condition is not always accepted. In these cases, the mixed cumulative logit model can be used, which will have more parameters. One of the classic problems that these models present is the lack of convergence due to the excess of parameters. This is one of the reasons why we group response categories together, which is also not always advisable. It is always recommended common sense in the grouping in such a way as not to lose the practical sense of the sensory evaluation.

REFERENCES

- AGRESTI, A. Analysis of ordinal categorical data. 2010. John Wiley & Sons.
- CHRISTENSEN, R. H. B.; Brockhoff, P. B. 2013. Analysis of sensory ratings data with cumulative link models. Journal de la Societe Francaise de Statistique & Revue de Statistique Appliquee, Société Francaise de Statistique, v. 154, n. 3, p. 58–79.
- FATORETTO, M. B., DE LARA, I. A. R., LORO, A. C., E SPOTO, M. H. F. 2018. Sensory evaluation of dehydrated tomatoes using the proportional odds mixed model. **Journal of food processing and preservation**, 42(11): e13822.
- JOHNSON, R. A.; WICHERN, D. W. 2008. Applied multivariate statistical analysis. Prentice hall Upper Saddle River, NJ, v. 5.
- KHURI, A. I.; CORNELL, J. A. 2018. **Response Surfaces: Design and Analyses**. 2nd. Taylor & Francis.
- LEMOS, T. D. O.; RODRIGUES, M. D. C. P.; LARA, I. A. R. D.; ARAÚJO, A. M. S. D.; LEMOS, T. L. G. D.; PEREIRA, A. L. F.; PAULA, L. V. T. D. 2015. Modeling the acceptability of cashew apple nectar brands using the proportional odds model. **Journal of Sensory Studies**, Wiley Online Library, v. 30, n. 2, p. 136–144.
- MOLENBERGHS, G., VERBEKE, G. 2006.

 Models for discrete longitudinal data,
 Springer Science & Business Media.
- MONTGOMERY, D. C. 2013. **Design and Analysis of Experiments**. Wiley & Sons.
- PEREIRA, A. L. F.; ALMEIDA, F. D. L.; JESUS, A. L. T. DE; COSTA, J. M. C. DA; RODRIGUES, S. 2013. Storage stability and acceptance of probiotic beverage from cashew apple juice. Food and bioprocess technology, Springer, v. 6, n. 11, p. 3155–3165.
- R CORE TEAM. 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

- REBOUÇAS, M. C. 2016. Bebida prebiótica à base de amêndoa da castanha de caju: estudos com consumidores em diferentes abordagens para avaliação de fatores sensoriais e externos ao produto. Tese (Doutorado) Universidade Federal do Ceará.
- TEIXEIRA, L. V. 2009. Análise sensorial na indústria de alimentos. **Revista do Instituto de Laticínios Cândido Tostes**, 64(366) 12-21.
- TUTZ, G. 2012. **Regression for categorical data**. Cambridge University Press.
- YEE, T. 2019. **VGAM package**: Vector generalized linear and additive models. R package.