Integra: Journal of Integrated Mathematics and Computer Science 2(2) 33-40

Integra: Journal of Integrated Mathematics and Computer Science

Journal Homepage: https://integrajimcs.com/index.php/integra/index

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Journal of Integrated Mathematics and Computer Science

Research Paper

Multidimensional Log-Linear Modeling (Case Study: Gender, Age, Head Circumference, and Nutritional Status Among Early Childhood Children)

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Keywords

Log-linear Model, Categorical Data, Interaction, Nutritional Status

Abstract

Poor nutritional status tends to increase the risk of morbidity and mortality among children in developing countries. Therefore, data on these rates can be an important indicator in describing the condition of undernutrition in a community. Log-linear model analysis can be used to categorize data on nutritional status. Based on data obtained from the Rajabasa Indah Health Center area, Rajabasa Subdistrict, Bandar Lampung City, there are 418 children who have examined at the Posyandu. The analysis model conducted in this study involves four variables, each variable is categorized into several categories according to predetermined criteria. Gender with two categories (male and female), age with two categories (1-12 months and 13-60 months), head circumference with two categories (normal and abnormal), and nutritional status with three categories (undernourished, well-nourished, and overnourished). This study aims to determine the best model using log-linear analysis that can explain the relationship between the four variables. The results obtained are the best model for the data involved in the [UG][LG][J] structure, the structure describes the interaction between age and nutritional status and head circumference and nutritional status.

Received: 13 May 2025, Accepted: 20 July 2025

https://doi.org/10.26554/integra.20252228

1. INTRODUCTION

A statistical model is a mathematical representation of the relationships between variables in a phenomenon. These models are used to understand, predict, and make decisions based on data. Some commonly used statistical models include linear regression, logistic regression, analysis of variance (ANOVA), multiple regression analysis, time series models, and others. These models have wide applications in various fields such as business, health, social sciences, and science. Some examples of the use of statistical models include research related to variants of regression analysis, namely robust regression [1, 2], geographically weighted regression [3, 4], and many more.

The log-linear model another statistical model which is an extension of two-dimensional contingency table analysis in which response and predictor variables are not distinguished. This model uses the logarithm of cell frequencies in the contingency table to analyze the relationships among categorical response variables [5]. In log-linear modeling, there is a type known as multidimensional log-linear modeling, which is used to analyze the relationships among more than two categorical variables. By applying a logarithmic transformation to the frequency data, this model enables researchers to explore interactions among variables in a more comprehensive manner [6]. Multidimensional log-linear models offer several advantages that make them more effective, especially in analyzing categorical data involving more than two variables [7, 8].

The log-linear model focuses more on categorical variables, multiple regression is used to predict the value of a dependent variable based on one or more independent variables. However, multiple regression has certain limitations, especially when applied to categorical data or when there are significant interactions between variables [9, 10, 11]. Although both methods can be used to analyze relationships between variables, log-linear models and multiple regression are often used to examine the relationship between nutritional status and related factors [12].

Factors influencing child nutrition can be categorized into more than one group. For example, gender is one factor that affects the nutritional status of children, with data categorized as male and female [13]. In this case, to facilitate the observation of patterns or relationships between variables such as gender and nutritional status, a contingency table is used.

A contingency table is a table that summarizes joint frequencies of observations made in each category of variables and is used to evaluate how two variables from their respective categories interact with each other [14]. Contingency tables can vary from two-dimensional to three-dimensional, from three-dimensional to four-dimensional, and so on. In this context, dimension is a term used to describe the number of factors or variables involved in influencing a case or phenomenon being analyzed [15].

Several studies have previously explored the application of log-linear models in various contexts. Satria et al. [16] investigated the application of log-linear models in analyzing two-way contingency tables. In the context of pandemic data, Suciati et al. [17] conducted a study on the application of log-linear models to COVID-19 data in Indonesia. Similarly, Jihyeok et al. [18] developed a log-linear model for delivery load analysis aimed at improving water quality through the TMDL framework in the Gyeongan Stream Watershed, Republic of Korea. In the medical field, Cuesta-Herrera et al. [19] utilized log-linear modeling to examine the interactions between risk factors associated with human papillomavirus (HPV) infection and Papanicolaou smear abnormalities. Moreover, Santi et al. [20] implemented a negative binomial log-linear model to analyze high school dropout data.

Poor nutritional status tends to increase morbidity and mortality rates among children under five in developing countries. Therefore, these figures can provide important information about the state of malnutrition in the community [21, 22]. The results of the Indonesian Toddler Nutrition Status Study (SSGBI) in 2019 showed that the prevalence of stunting among toddlers decreased from 37.2% in 2013 to 30.8% in 2018, and further declined to 27.67% in 2019. Additionally, the prevalence of wasting decreased from 7.44% to 2.76% during the same period. However, the stunting prevalence remains high and has not yet reached the target set by the World Health Organization (WHO), which is below 20% [22, 23, 24]. Based on the background above, this study will analyze a four-dimensional multidimensional log-linear model to determine the relationships among four observed variables: gender, child's age, head circumference, and nutritional status in early childhood within the Rajabasa Indah Community Health Center area.

2. METHODS

The data used in this study are secondary data consisting of gender, age, head circumference, and nutritional status of children in the Rajabasa Indah Community Health Center area in 2024. The categorization of each variable in this study is as follows: gender (male and female), age (infants 0–12 months and toddlers 13–60 months), head circumference (normal and abnormal), and nutritional status (under-nutrition, normal nutrition, and over-nutrition).

The objective of this study is to explain the analysis procedure using a multidimensional log-linear model and to determine the best model in describing children's nutritional status based on age, gender, head circumference, and nutritional status. This study also aims to identify the relationships or interactions among these four variables. The data used in this study are processed using the SAS program, and the analysis steps are as follows:

1. Use descriptive statistics to analyze the proportional characteristics of the data.
2. Develop the best four-dimensional log-linear model through the following steps:
   a) Enumerate all possible models formed by the four variables, from the simplest to the most complex.
   b) Determine the frequency distribution.
   c) To ensure that the model is applicable or fits well, perform goodness-of-fit or significance tests.
   d) Calculate the Akaike's Information Criterion (AIC) value for each model.
   e) Examine the smallest AIC value among the suitable models to select the best one.
3. Model interpretation stage:
   a) Interpret the parameters of the best model.
   b) Calculate the odds ratios.
   c) Draw conclusions regarding the relationships among the variables and factors.

3. RESULT AND DISCUSSIONS

3.1 Descriptive Analysis

Descriptive statistics were used to identify the nutritional characteristics of infants and toddlers in the Rajabasa Indah Community Health Center area, Rajabasa District, Bandar Lampung City, in 2024, based on four variables: gender, child's age, head circumference, and nutritional status. Of the 418 samples obtained, 233 infants and toddlers were male, while 185 were female. Based on the nutritional status variable of infants and toddlers, 12.68% were classified as undernourished, 72.01% had normal nutritional status, and 15.31% were classified as overnourished. It is evident that there is a considerable difference between the proportion of children with normal nutritional status and those who are undernourished or overnourished. Figure 1 shows the number of groups with under nutrition status based on gender and head circumference, Figure 2 displays the number of age groups with good nutritional status based on gender and head circumference, and Figure 3 displays the number of age groups with over nutritional status based on gender and head circumference.

It is known that 6.94% of infants and toddlers with undernutrition had a normal head circumference, consisting of 0.48% male infants, 3.35% male toddlers, 0.48% female infants, and 2.63% female toddlers. Additionally, 5.74% of infants and toddlers with undernutrition had an abnormal head circumference, comprising

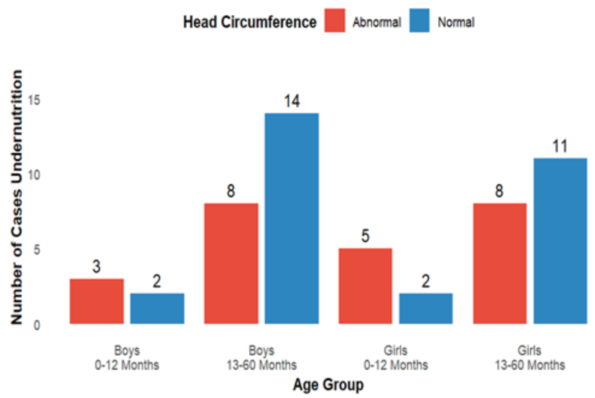

Figure 1. The Number of Age Groups with Undernutrition Status Based on Gender and Head Circumference

0.72% male infants, 1.91% male toddlers, 1.20% female infants, and 1.91% female toddlers.

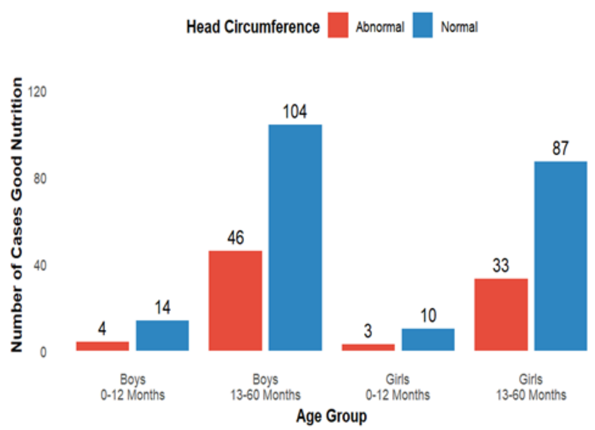

Figure 2. The Number of Age Groups with Good Nutritional Status Based on Gender and Head Circumference

A total of 72.01% of infants and toddlers had good nutritional status. Among them, 51.44% had a normal head circumference, consisting of 3.35% male infants, 24.88% male toddlers, 2.40% female infants, and 20.81% female toddlers. Meanwhile, 20.57% of infants and toddlers with good nutritional status had an abnormal head circumference, including 0.96% male infants, 11.00% male toddlers, 0.72% female infants, and 7.89% female toddlers.

The figure shows that 15.31% of infants and toddlers had overnutrition. Among them, 9.09% had a normal head circumference, consisting of 2.39% male infants, 2.15% male toddlers, 0.72% female infants, and 3.83% female toddlers. In addition, 6.22% of infants and toddlers with overnutrition had an abnormal head circumference, comprising 1.67% male infants, 2.87% male toddlers, 0.48% female infants, and 1.20% female toddlers.

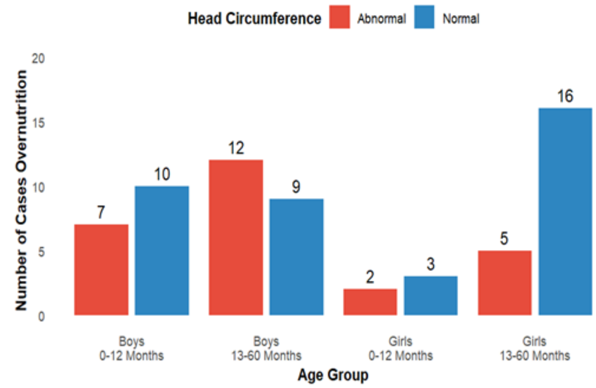

Figure 3. The Number of Age Groups with Good Nutritional Status Based on Gender and Head Circumference

3.2 Development of the Four-Dimensional Log-linear Model

The four-dimensional log-linear model is constructed by considering all possible interactions among the four variables analyzed, namely gender (J), child's age (U), head circumference (L), and nutritional status (G). In this approach, the saturated model includes various interactions, starting from the main effects of each variable (first-order interactions), interactions between pairs of variables (second-order interactions), interactions involving three variables simultaneously (third-order interactions), up to the most complex interaction involving all four variables together (higher-order interaction). This approach aims to comprehensively identify the pattern of relationships among the variables.

3.3 Frequency Distribution

Frequency distribution is obtained by summing the values of the density function calculated for each category. The results of these calculations are then used to provide a clearer representation of the data distribution based on the specified categories [22]. Based on Appendix A, a total of 84 frequency cells were obtained from the contingency table. The smallest subtotal is found in the equation $n_{+111} = 4$, indicating the number of observations for infants aged 0–12 months with normal head circumference who have undernutrition status across all genders. Meanwhile, the largest subtotal is in the equation $n_{++++} = 418$, representing the total number of observations for all categories across all variables. Differences in categories within each variable lead to variations in the estimated values of the likelihood equations.

3.4 Goodness-of-Fit Test Results

The goodness-of-fit test was conducted to determine whether a model is significant based on the test statistic used, namely the likelihood ratio test (G^2) [23]. In the four-dimensional log-linear model, there are 114 possible models formed. The goodness-of-fit test results for each model can be found in Appendix B, where H_0 represents the fitted model and H_1 represents the non-fitted model, at a 5% significance level, out of the 114 models formed,

Appendix A. The Total of the Density Functions Calculated for Each Category

$n_{++++} = 418$	$n_{2+2+} = 56$	$n_{++11} = 29$	$n_{22+1} = 19$	$n_{1+13} = 19$
$n_{1+++} = 233$	$n_{1++1} = 27$	$n_{++21} = 24$	$n_{11+2} = 18$	$n_{1+23} = 19$
$n_{2+++} = 185$	$n_{2++1} = 26$	$n_{++12} = 215$	$n_{12+2} = 150$	$n_{2+13} = 19$
$n_{+1++} = 65$	$n_{1++2} = 168$	$n_{++22} = 86$	$n_{21+2} = 13$	$n_{2+23} = 7$
$n_{+2++} = 353$	$n_{2++2} = 133$	$n_{++13} = 38$	$n_{22+2} = 120$	$n_{+111} = 4$
$n_{++1+} = 282$	$n_{1++3} = 38$	$n_{++23} = 26$	$n_{11+3} = 17$	$n_{+121} = 8$
$n_{++2+} = 136$	$n_{2++3} = 26$	$n_{111+} = 26$	$n_{12+3} = 21$	$n_{+211} = 25$
$n_{+++1} = 53$	$n_{+11+} = 41$	$n_{121+} = 127$	$n_{21+3} = 5$	$n_{+221} = 16$
$n_{+++2} = 301$	$n_{+21+} = 241$	$n_{211+} = 15$	$n_{22+3} = 21$	$n_{+112} = 24$
$n_{+++3} = 64$	$n_{+12+} = 24$	$n_{221+} = 114$	$n_{1+11} = 16$	$n_{+122} = 7$
$n_{11++} = 40$	$n_{+22+} = 112$	$n_{112+} = 14$	$n_{1+21} = 11$	$n_{+212} = 191$
$n_{21++} = 25$	$n_{+1+1} = 12$	$n_{122+} = 66$	$n_{2+11} = 13$	$n_{+222} = 79$
$n_{12++} = 193$	$n_{+2+1} = 41$	$n_{212+} = 10$	$n_{2+21} = 13$	$n_{+113} = 13$
$n_{22++} = 160$	$n_{+1+2} = 31$	$n_{222+} = 46$	$n_{1+12} = 118$	$n_{+123} = 9$
$n_{1+1+} = 153$	$n_{+2+2} = 270$	$n_{11+1} = 5$	$n_{1+22} = 50$	$n_{+213} = 25$
$n_{2+1+} = 129$	$n_{+1+3} = 22$	$n_{12+1} = 22$	$n_{2+12} = 97$	$n_{+223} = 17$
$n_{1+2+} = 80$	$n_{+2+3} = 42$	$n_{21+1} = 7$	$n_{2+22} = 36$	

68 models were found to be significant, as indicated by p-values greater than 0.05. Therefore, it can be concluded that these 68 models adequately fit the observed data.

3.5 Determining the AIC Value

After obtaining 68 significant models based on the analysis performed, the next step is to select the best model using the Akaike's Information Criterion (AIC) method. AIC is a commonly used method in statistical model selection, where the best model is determined by identifying the model with the smallest AIC value. Table 1 displays the selected model with the lowest AIC.

$$AIC = G^2 - 2d$$

The AIC values for each model are presented in Appendix C.

3.6 Determining the Best Model

Based on the AIC values calculated for each model in Appendix 3, the best model is identified as the [UG][LG][J] model, which has the smallest AIC value of -12.79. Subsequently, the multidimensional log-linear model equation for the best model [UG][LG][J] will be constructed based on the maximum likelihood analysis of variance to examine the relationships among the variables. Table 2 shows the maximum likelihood analysis of variance for the best model.

Based on Table 2, it is known that the best model [UG][LG][J] has the following model equation:

$$\log m_{abcd} = \mu + \lambda_a^j + \lambda_b^U + \lambda_c^L + \lambda_d^G + \lambda_{bd}^{UG} + \lambda_{cd}^{LG}$$

Gender (J) is significant at the 0.05 level, indicating its contribution to the model. Age (U) and nutritional status (G) are highly significant, highlighting their influence on data distribution. Head circumference (L) is significant individually, and its interaction with nutritional status (LG) is also important. The interaction between age and nutritional status (UG) is highly significant, demonstrating a strong relationship. The likelihood ratio for the best model [UG][LG][J] (Table 1) exceeds 0.05, indicating a good model fit.

3.7 Factor Interactions in the Best-Fitting Model

Previously, the best multidimensional log-linear model identified was [UG][LG][J]. This model indicates two two-way interactions: one between age and nutritional status, and another between head circumference and nutritional status. Figure 4 displays the interaction between age and nutritional status, while Figure 5 shows the interaction of head circumference with nutritional status.

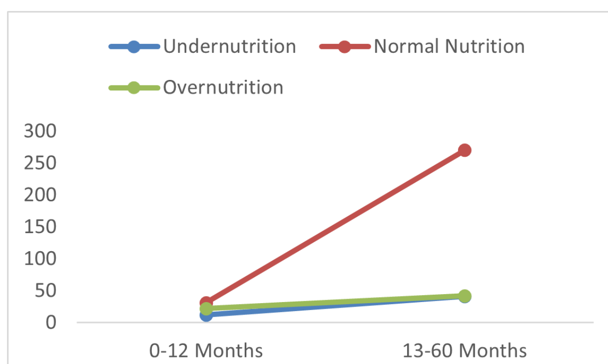

Figure 4. Interaction Between Age and Nutritional Status

That figure illustrates the interaction between age and nutritional status. As age increases, there is a noticeable rise in the proportion of individuals experiencing undernutrition. Simulta-

Appendix B. Goodness of Fit Test in a Four-Dimensional Log-Linear Model

No	Model	Likelihood Ratio	*df*	*p*-value	Decision	No	Model	Likelihood Ratio	*df*	*p*-value	Decision
1	(J,U,L,G)	45.55	18	0.0003	Reject H_0	58	(JU,JL,JG,UL,UG)	19.77	11	0.0485	Reject H_0
2	(JU,L,G)	44.49	17	0.0003	Reject H_0	59	(JU,JL,JG,UL,LG)	34.44	11	0.0003	Reject H_0
3	(JL,U,G)	44.77	17	0.0002	Reject H_0	60	(JU,JL,JG,UG,LG)	12.53	10	0.2511	Do not reject H_0
4	(JG,U,L)	44.71	16	0.0001	Reject H_0	61	(JU,JL,UL,UG,LG)	13.39	11	0.2687	Do not reject H_0
5	(UL,J,G)	44.88	17	0.0002	Reject H_0	62	(JU,JG,UL,UG,LG)	13.33	10	0.2057	Do not reject H_0
6	(UG,J,L)	22.97	16	0.1144	Do not reject H_0	63	(JL,JG,JL,UG,LG)	12.53	10	0.2510	Do not reject H_0
7	(LG,J,U)	37.78	16	0.0016	Reject H_0	64	(JU,JL,JG,UL,UG,LG)	12.50	9	0.1866	Do not reject H_0
8	(JU,LG)	36.72	15	0.0014	Reject H_0	65	(JUL,G)	42.46	14	0.0001	Reject H_0
9	(JL,UG)	22.19	15	0.1028	Do not reject H_0	66	(JUG,L)	16.88	11	0.1115	Do not reject H_0
10	(JG,UL)	44.05	15	0.0001	Reject H_0	67	(JLG,U)	32.73	11	0.0006	Reject H_0
11	(JU,JL,G)	43.71	16	0.0002	Reject H_0	68	(ULG,J)	11.69	11	0.3870	Do not reject H_0
12	(JU,JG,L)	43.65	15	0.0001	Reject H_0	69	(JUL,JUG)	14.85	8	0.0622	Do not reject H_0
13	(JU,UL,G)	43.82	16	0.0002	Reject H_0	70	(JUL,JLG)	30.42	8	0.0002	Reject H_0
14	(JU,UG,L)	21.92	15	0.1100	Do not reject H_0	71	(JUL,ULG)	9.27	8	0.3201	Do not reject H_0
15	(JL,JG,U)	43.93	15	0.0001	Reject H_0	72	(JUG,JLG)	4.90	6	0.5571	Do not reject H_0
16	(JL,UL,G)	44.10	16	0.0002	Reject H_0	73	(JUG,ULG)	5.60	6	0.4697	Do not reject H_0
17	(JL,LG,U)	37.00	15	0.0013	Reject H_0	74	(JLG,ULG)	6.64	6	0.3551	Do not reject H_0
18	(JG,UG,L)	22.14	14	0.0758	Do not reject H_0	75	(JUL,JUG,JLG)	3.76	4	0.4398	Do not reject H_0
19	(JG,LG,U)	36.94	14	0.0007	Reject H_0	76	(JUL,JUG,ULG)	4.20	4	0.3793	Do not reject H_0
20	(UL,UG,J)	22.31	15	0.0999	Do not reject H_0	77	(JUG,JLG,ULG)	1.33	3	0.7229	Do not reject H_0
21	(UL,LG,J)	37.12	15	0.0012	Reject H_0	78	(JUL,JLG,ULG)	4.53	4	0.3387	Do not reject H_0
22	(UG,LG,J)	15.21	14	0.3641	Do not reject H_0	79	(JUL,JUG,JLG,ULG)	0.65	2	0.7216	Do not reject H_0
23	(JU,JL,JG)	42.87	14	<0.0001	Reject H_0	80	(JUL,JG)	41.62	12	<0.0001	Reject H_0
24	(JU,UL,UG)	21.25	14	0.0953	Do not reject H_0	81	(JUL,UG)	19.88	12	0.0693	Do not reject H_0
25	(JL,UL,LG)	36.34	14	0.0009	Reject H_0	82	(JUL,LG)	34.69	12	0.0005	Reject H_0
26	(JG,UG,LG)	14.37	12	0.2777	Do not reject H_0	83	(JUG,JL)	16.10	10	0.0968	Do not reject H_0
27	(JU,JL,UG)	21.14	14	0.0982	Do not reject H_0	84	(JUG,UL)	16.21	10	0.0936	Do not reject H_0
28	(JU,JL,LG)	35.94	14	0.0010	Reject H_0	85	(JUG,LG)	9.11	9	0.4271	Do not reject H_0
29	(JU,JG,UL)	42.99	14	<0.0001	Reject H_0	86	(JLG,JU)	31.67	10	0.0004	Reject H_0
30	(JU,JG,LG)	35.89	13	0.0006	Reject H_0	87	(JLG,UL)	32.07	10	0.0003	Reject H_0
31	(JU,UL,LG)	36.06	14	0.0010	Reject H_0	88	(ULG,JU)	10.64	10	0.3865	Do not reject H_0
32	(JU,UG,LG)	14.15	13	0.3634	Do not reject H_0	89	(ULG,JL)	10.92	10	0.3641	Do not reject H_0
33	(JL,JG,UL)	43.27	14	<0.0001	Reject H_0	90	(ULG,JG)	10.86	9	0.2865	Do not reject H_0
34	(JL,JG,UG)	21.36	13	0.0661	Do not reject H_0	91	(JUL,JUG,LG)	7.50	6	0.2773	Do not reject H_0
35	(JL,UL,UG)	21.53	14	0.0887	Do not reject H_0	92	(JUL,JLG,UG)	7.92	6	0.2437	Do not reject H_0
36	(JL,UG,LG)	14.43	13	0.3443	Do not reject H_0	93	(JUL,ULG,JG)	8.51	6	0.2028	Do not reject H_0
37	(JG,UL,UG)	21.47	13	0.0641	Do not reject H_0	94	(JUG,JLG,UL)	4.89	5	0.4294	Do not reject H_0
38	(JG,UL,LG)	36.28	13	0.0005	Reject H_0	95	(JUG,ULG,JL)	4.58	5	0.4686	Do not reject H_0
39	(JU,JL,UL,G)	43.11	15	0.0001	Reject H_0	96	(JLG,ULG,JU)	5.45	5	0.3629	Do not reject H_0
40	(JU,JG,UG,L)	21.15	13	0.0700	Do not reject H_0	97	(JUL,JG,UG,LG)	11.84	8	0.1583	Do not reject H_0
41	(JL,JG,LG,U)	36.09	13	0.0006	Reject H_0	98	(JUG,JL,UL,LG)	8.23	7	0.3130	Do not reject H_0
42	(UL,UG,LG,J)	15.16	13	0.2977	Do not reject H_0	99	(JLG,JU,UL,UG)	9.14	7	0.2426	Do not reject H_0
43	(JU,JL,UL,LG)	35.35	13	0.0007	Reject H_0	100	(ULG,JU,JL,JG)	9.04	7	0.2499	Do not reject H_0
44	(JU,JL,JG,UG)	20.37	12	0.0604	Do not reject H_0	101	(JUL,UL,LG)	34.69	12	0.0005	Reject H_0
45	(JU,JL,JG,LG)	35.03	12	0.0005	Reject H_0	102	(JUG,UL,LG)	9.06	8	0.3373	Do not reject H_0
46	(JU,JL,UL,UG)	20.54	13	0.0825	Do not reject H_0	103	(JLG,UL,UG)	10.10	8	0.2577	Do not reject H_0
47	(JU,JL,JG,UL)	42.28	13	<0.0001	Reject H_0	104	(ULG,JL,JG)	10.01	8	0.2646	Do not reject H_0
48	(JU,JL,UG,LG)	13.42	12	0.3391	Do not reject H_0	105	(ULG,JU,JL)	9.93	9	0.3565	Do not reject H_0
49	(JU,JG,UL,UG)	20.49	12	0.0584	Do not reject H_0	106	(ULG,JU,JG)	9.87	8	0.2743	Do not reject H_0
50	(JU,JG,UL,LG)	35.22	12	0.0004	Reject H_0	107	(JLG,JU,UL)	31.08	9	0.0003	Reject H_0
51	(JU,JG,UG,LG)	13.38	11	0.2690	Do not reject H_0	108	(JLG,JU,UG)	9.17	8	0.3283	Do not reject H_0
52	(JU,UL,UG,LG)	14.10	12	0.2945	Do not reject H_0	109	(JUG,JL,UL)	15.50	9	0.0780	Do not reject H_0
53	(JL,JG,UL,UG)	20.70	12	0.0549	Do not reject H_0	110	(JUG,JL,LG)	8.26	8	0.4085	Do not reject H_0
54	(JL,JG,UL,LG)	35.43	12	0.0004	Reject H_0	111	(JUL,JG,UG)	19.12	10	0.0387	Reject H_0
55	(JL,JG,UG,LG)	13.52	11	0.2608	Do not reject H_0	112	(JUL,JG,LG)	33.78	10	0.0002	Reject H_0
56	(JL,UL,UG,LG)	14.38	12	0.2772	Do not reject H_0	113	(JULG)	0	0	0	Reject H_0
57	(JG,UL,UG,LG)	14.32	11	0.2158	Do not reject H_0						

neously, the proportions of individuals with normal and excess nutritional status also show an upward trend. This suggests that as children grow, changes in dietary habits, lifestyle, and nutritional requirements become more apparent, contributing to a broader variation in nutritional outcomes across age groups.

FIGURE

Based on the figure, it can be concluded that there is a relationship between head circumference and nutritional status.

Appendix C. The AIC Value for the Significant Model

No	Model	Likelihood Ratio	*df*	AIC	No	Model	Likelihood Ratio	*df*	AIC
1	(UG,J,L)	22.97	16	-9.03	35	(JUL,ULG)	9.27	8	-6.73
2	(JL,UG)	22.19	15	-7.81	36	(JUG,JLG)	4.90	6	-7.10
3	(JU,UG,L)	21.92	15	-8.08	37	(JUG,ULG)	5.60	6	-6.40
4	(JG,UG,L)	22.14	14	-5.86	38	(JLG,ULG)	6.64	6	-5.36
5	(UL,UG,J)	22.31	15	-7.69	39	(JUL,JUG,JLG)	3.76	4	-4.24
6	(UG,LG,J)	15.21	14	-12.79	40	(JUL,JUG,ULG)	4.20	4	-3.80
7	(JU,UL,UG)	21.25	14	-6.75	41	(JUG,JLG,ULG)	1.33	3	-4.67
8	(JG,UG,LG)	14.37	12	-9.63	42	(JUL,JLG,ULG)	4.53	4	-3.47
9	(JU,JL,UG)	21.14	14	-6.86	43	(JUL,JUG,JLG,ULG)	0.65	2	-3.35
10	(JU,UG,LG)	14.15	13	-11.85	44	(JUL,UG)	19.88	12	-4.12
11	(JL,JG,UG)	21.36	13	-4.64	45	(JUG,JL)	16.10	10	-3.90
12	(JL,UL,UG)	21.53	14	-6.47	46	(JUG,UL)	16.21	10	-3.79
13	(JL,UG,LG)	14.43	13	-11.57	47	(JUG,LG)	9.11	9	-8.89
14	(JG,UL,UG)	21.47	13	-4.53	48	(ULG,JU)	10.64	10	-9.36
15	(JU,JG,UG,L)	21.15	13	-4.85	49	(ULG,JL)	10.92	10	-9.08
16	(UL,UG,LG,J)	15.16	13	-10.84	50	(ULG,JG)	10.86	9	-7.14
17	(JU,JL,JG,UG)	20.37	12	-3.63	51	(JUL,JUG,LG)	7.50	6	-4.50
18	(JU,JL,UL,UG)	20.54	13	-5.46	52	(JUL,JLG,UG)	7.92	6	-4.08
19	(JU,JL,UG,LG)	13.42	12	-10.58	53	(JUL,ULG,JG)	8.51	6	-3.49
20	(JU,JG,UL,UG)	20.49	12	-3.51	54	(JUG,JLG,UL)	4.89	5	-5.11
21	(JU,JG,UG,LG)	13.38	11	-8.62	55	(JUG,ULG,JL)	4.58	5	-5.42
22	(JU,UL,UG,LG)	14.10	12	-9.90	56	(JLG,ULG,JU)	5.45	5	-4.55
23	(JL,JG,UL,UG)	20.70	12	-3.30	57	(JUL,JG,UG,LG)	11.84	8	-4.16
24	(JL,JG,UG,LG)	13.52	11	-8.48	58	(JUG,JL,UL,LG)	8.23	7	-5.77
25	(JL,UL,UG,LG)	14.38	12	-9.62	59	(JLG,JU,UL,UG)	9.14	7	-4.86
26	(JG,UL,UG,LG)	14.32	11	-7.68	60	(ULG,JU,JL,JG)	9.04	7	-4.96
27	(JU,JL,JG,UG,LG)	12.53	10	-7.47	61	(JUG,UL,LG)	9.06	8	-6.94
28	(JU,JL,UL,UG,LG)	13.39	11	-8.61	62	(JLG,UL,UG)	10.10	8	-5.90
29	(JU,JG,UL,UG,LG)	13.33	10	-6.67	63	(ULG,JL,JG)	10.01	8	-5.99
30	(JL,JG,JL,UG,LG)	12.53	10	-7.47	64	(ULG,JU,JL)	9.93	9	-8.07
31	(JU,JL,JG,UL,UG,LG)	12.50	9	-5.50	65	(ULG,JU,JG)	9.87	8	-6.13
32	(JUG,L)	16.88	11	-5.12	66	(JLG,JU,UG)	9.17	8	-6.83
33	(ULG,J)	11.69	11	-10.31	67	(JUG,JL,UL)	15.50	9	-2.50
34	(JUL,JUG)	14.85	8	-1.15	68	(JUG,JL,LG)	8.26	8	-7.74

Table 1. Selected Model with the Lowest AIC

Model	Likelihood Ratio	*df*	*AIC*
(UG,LG,J)	15.21	14	-12.79

Infants and toddlers with head circumference within the normal range are more likely to have good nutritional status, whereas those with abnormal head circumference tend to have a higher risk of undernutrition.

3.8 Estimation of Odds Ratios

For the best-fitting model [UG][LG][J], a significant interaction was observed between head circumference and nutritional status. Therefore, the calculation of the odds ratio is specifically focused on the relationship between head circumference (L) and

Table 2. Maximum Likelihood Analysis of Variance for the Best Model

Source	*df*	Chi-Square	Pr > ChiSq
U	1	76.64	<0.0001
G	2	65.18	<0.0001
U*G	2	23.22	<0.0001
L	1	14.03	0.0002
L*G	2	7.86	0.0197
J	1	5.49	0.0192
Likelihood ratio	14	15.21	0,3641

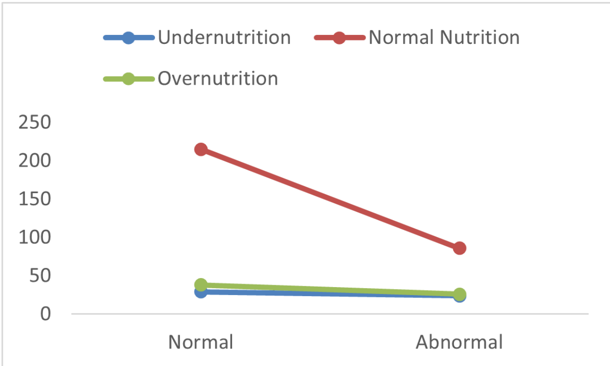

Figure 5. Interaction Between Head Circumference and Nutritional Status

nutritional status (G), excluding gender (J) from this particular analysis. However, to obtain a more detailed and comprehensive understanding of this relationship, the analysis is still conducted separately based on age groups (U).

Table 3. Partial Odds Ratio of Nutritional Status and Head Circumference Based on Age 0–12 Months

Comparison of Nutritional Status	Odds Ratio	95% CI OR
Undernutrition vs Normal Nutrition	2	1.10 − 3.09
Normal Nutrition vs Overnutrition	2.35	0.71 − 7.77
Overnutrition vs Undernutrition	3.41	0.78 − 14.84

It can be observed that the odds of infants with abnormal head circumference having undernutrition are approximately twice (or 200%) the odds of infants with normal head circumference having undernutrition. Additionally, the odds of infants with normal head circumference having normal nutrition are about 2.35 times (or 235%) the odds of those with abnormal head circumference having normal nutrition. Furthermore, the odds of infants with normal head circumference having overnutrition are approximately 3.41 times (or 341%) the odds of infants with abnormal head circumference having overnutrition. Table 3 shows the partial odd ratio of nutritional status and head circumference based on age 0 − 12 months, while Table 4 displays the partial odd ratio of nutritional status and head circumference based on age 13 − 60 months

It can be seen that the odds of toddlers with abnormal head circumference having undernutrition are approximately 1.43 times (or 143%) the odds of toddlers with normal head circumference having undernutrition. Meanwhile, the odds of toddlers with normal head circumference having normal nutrition are about 1.61 times (or 161%) the odds of toddlers with abnormal head circumference having normal nutrition. Additionally, the odds of toddlers with normal head circumference having overnutrition are approximately 0.96 times (or 96%) the odds of toddlers with abnormal head circumference having overnutrition.

Table 4. Partial Odds Ratio of Nutritional Status and Head Circumference Based on Age 13–60 Months

Comparison of Nutritional Status	Odds Ratio	95% CI OR
Undernutrition vs Normal Nutrition	1.43	0.72 − 2.82
Normal Nutrition vs Overnutrition	1.61	0.82 − 3.14
Overnutrition vs Undernutrition	0.96	0.39 − 2.31

4. CONCLUSIONS

Based on the results and discussion presented in the previous chapter, it can be concluded that the best-fitting model using the four-dimensional multidimensional log-linear analysis is the [UG][LG][J] model, represented by the following equation:

$$\log m_{abcd} = \mu + \lambda_a^j + \lambda_b^U + \lambda_c^L + \lambda_d^G + \lambda_{bd}^{UG} + \lambda_{cd}^{LG}$$

The best-fitting model [UG][LG][J] indicates relationships between age and nutritional status [UG], as well as head circumference and nutritional status [LG]. Based on the odds ratio values, it is found that the age category of 0–12 months with normal head circumference has the highest odds ratio—approximately 3.41 times greater likelihood of experiencing overnutrition compared to those with abnormal head circumference

5. ACKNOWLEDGEMENT

The author would like to thank Mr. Prof. Drs. Mustofa Usman, M.A., P.hD., Mrs. Siti Laelatul Chasanah, S.Pd., M.Si., Mrs. Widiarti, S.Si., M.Si. who have supported and assisted in the preparation of this paper.

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