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PREDICTING THE ACCURACY OF NON-CASH FOOD ASSISTANCE PROGRAM IN ACEH USING LOGISTIC REGRESSION BINER IN ACEH PROVINCE: HOW IS THE CONDITION?

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Abstract.

This study examines the effectiveness of the Non-Cash Food Assistance Program (BPNT) in alleviating poverty in Aceh Province, the poorest province on the island of Sumatra. The research utilizes data from the 2022 National Socioeconomic Survey (Susenas) to analyze household characteristics and determine factors influencing BPNT eligibility. Binary logistic regression and data balancing with SMOTE were applied to assess classification accuracy. Results indicate that households without adequate basic amenities, such as proper toilets and electricity, and those with limited access to resources, such as well water, firewood for cooking, and lack of household assets, are more likely to qualify for BPNT. The logistic regression model achieved an accuracy of 80.83%, with high recall for "Recipient" classification. This study findings highlight is that economic hardship, household size, and physical conditions are significant determinants of BPNT eligibility. This study suggests that targeted assistance for poverty alleviation can be optimized through refined eligibility criteria and data accuracy improvements.

Keywords : BPNT, Poverty, Logistic Regression Classification, Aceh Province

1. Introduction

The Non-Cash Food Assistance Program (BPNT) is one of the social assistance programs designed by the Indonesian government to help low-income families meet their food needs. This program provides financial support in the form of electronic money, which can only be used to purchase food at designated locations, such as Gotong Royong Electronic Warung (e-warong). The primary objective of BPNT is to improve food security for poor and vulnerable families in Indonesia. Since 2002, Aceh has been the poorest province on the island of Sumatra [1]. This has driven Aceh to continually rise from poverty, defined as the inability to meet basic needs. BPNT serves as a solution to poverty issues. By using a non-cash system, BPNT increases transparency and efficiency in the

distribution of aid, reduces the potential for misuse of social assistance, and ensures that the funds provided are used appropriately for food needs. The initial proposal for BPNT is recommended by the village, guiding residents to register for the assistance through their local village officials.

Each Beneficiary Family (KPM) receives assistance of Rp200,000 per month, disbursed every two months, totaling Rp400,000. To qualify for BPNT, individuals or families must meet certain requirements, including being Indonesian citizens (WNI) with official identification such as an ID card (KTP), being registered in the Integrated Social Welfare Data (DTKS) managed by the Ministry of Social Affairs, falling within the low-income category with income below the established minimum wage, not working as Civil Servants (ASN), members of the Indonesian National Armed Forces/Police, or employees of state/regional-owned enterprises (BUMN/BUMD), and not receiving other social assistance [2].

BPNT funds cannot be converted to cash and can only be used to purchase food items at designated e-warong. These items include staples such as rice, eggs, and other daily necessities. The program is expected to help improve community access to nutritious food and support government efforts in reducing poverty rates in Indonesia, particularly in Aceh. By understanding the criteria and registration process for BPNT, the public is expected to make optimal use of this assistance to improve family welfare.

The distribution of BPNT is expected to be equitable and precise, so development programs can be implemented effectively. This aligns with the second goal of the Sustainable Development Goals (SDGs), which is zero hunger [3]. Debates have arisen regarding BPNT's role in helping poor households meet their food needs. Proponents claim that BPNT improves previous food assistance by enhancing the targeting accuracy of KPM [4].

Research related to social assistance programs has been conducted, such as (5), who examined "The Effectiveness of the Non-Cash Food Assistance Program in Yogyakarta City" using primary data collected from respondents in Yogyakarta, focusing on the effectiveness of BPNT itself. However, there has not been specific research examining the distribution and factors influencing social assistance recipients, as well as the determinants of a household's eligibility for BPNT. Factors influencing BPNT recipients include economic conditions, employment, physical conditions of the home, and many other factors. So far, BPNT distribution is verified through DTKS data, which originates from the village. The accuracy of determining social assistance recipients remains low. Therefore, it is essential to conduct a study to analyze the distribution of BPNT recipients in Aceh statistically and identify the factors influencing BPNT eligibility, thus examining its distribution and relevance to poverty alleviation in Aceh Province. This study's novelty lies in obtaining an overview of BPNT distribution and the factors influencing eligibility across regions, linking it to the poverty rate in those areas, and understanding regional factors affecting BPNT eligibility in Aceh Province.

2. Literature Review

2.1. Poverty

According to Undang-undang No. 24 Tahun 2004, poverty is defined as the socioeconomic condition in which an individual or group is unable to fulfill their basic rights to maintain and develop a dignified life. The Central Bureau of Statistics (BPS) or Office for National Statistics (ONS) defines poverty as the inability to meet basic food and non-food needs, measured by expenditure. Poor individuals are those with an average monthly per capita expenditure below the poverty line. The handling of poor or destitute individuals is further elaborated in Undang-undang No. 13 Tahun 2011, which states that destitute individuals are entitled to social protection, adequate food, clothing, and healthcare services to ensure a better life. To achieve these rights, the Indonesian government has established criteria for destitute and low-income households according to Minister of Social Affairs Regulation No. 146 of 2013 (Keputusan Menteri Sosial RI No 146 Tahun 2013).

In addition to the criteria outlined in Minister of Social Affairs Regulation No. 146 of 2013, research by [6] shows a positive correlation between poverty and household size, particularly when there are many non-productive household members. If household income does not increase proportionally with the number of dependents, the household will become poorer. The presence of young children and school-age members further adds to household burdens, as food, clothing, healthcare, and education expenses are substantial.

Poverty in a household can be easily identified by examining the household's living conditions, such as floor, wall, and roof materials [7]. Apart from housing factors, other supporting factors, such as lighting and water access, also play a role. In terms of regional development, poor households tend to reside in impoverished areas with inadequate facilities like lighting and clean water [8].

2.2. Social Assistance

Social protection encompasses policies, programs, and actions taken by the government and society to provide security and support to individuals or groups in need, enabling them to overcome poverty and social risks. In Indonesia, the social protection system consists of social security and social assistance. As a system, social protection plays a crucial role in poverty alleviation and reducing inequality. Social security aims to mitigate risks by providing income support or insurance coverage, while social assistance is designed to improve social welfare by eradicating poverty. The primary objective of social protection is to enhance social welfare and reduce poverty.

According to the International Labour Organization (ILO), social protection is part of social policy aimed at ensuring income security and access to social services for all individuals, with special attention to vulnerable groups, while protecting and empowering communities. The guaranteed elements include: 1) Basic income security, pension funds for the elderly and disabled, income support, and job guarantees for the unemployed and the poor; 2) Universal access to affordable social services in health, water and sanitation, education, food security, and other national priorities [9].

2.3. Non-Cash Food Assistance or Bantuan Pangan Non Tunai (BPNT)

According to the 2019 General Guidelines for BPNT [10], based on Presidential Regulation No. 63 of 2017 concerning the Distribution of Non-Cash Social Assistance, non-cash food assistance (BPNT) is a form of social food assistance distributed in non-cash form by the government. It is provided to Beneficiary Families (KPM) each month through an electronic money mechanism, which can only be used to purchase food items from food vendors, referred to as E-Warong, in cooperation with the designated distributing bank. Previously, this assistance was known as subsidized rice or "Rastra rice." As decided in the limited meeting on March 16, 2016, concerning the Poverty and Economic Inequality Reduction Program, it was agreed that starting in the 2017 fiscal year, the distribution of Rastra benefits (later referred to as Non-Cash Food Assistance/BPNT) would be carried out through a non-cash mechanism (using e-voucher technology) to ensure better targeting and accessibility.

The objectives of the BPNT program, as outlined in the general guidelines, include reducing the expenditure burden on KPM by partially fulfilling their food needs, providing more balanced nutrition to KPM, improving the accuracy of targeting and the timeliness of food assistance delivery to KPM, giving KPM more choice and control in meeting their food needs, and supporting the achievement of Sustainable Development Goals (SDGs) [10,11].

2.4. Logistic Regression Biner

Logistic regression is a method used to determine the relationship between predictor variables and a response variable that has two or more categories. Logistic regression is classified into three types: binary logistic regression, multinomial logistic regression, and ordinal logistic regression [12]. Binary logistic regression is used when the response variable has two categories (dichotomous). In contrast, multinomial logistic regression is used for a response variable with more than two categories (polychotomous). Ordinal logistic regression, on the other hand, is applied when the response variable is ordinally scaled. According to Hosmer and Lemeshow (2020) [13], logistic regression is a method that connects a categorical dependent variable with independent variables. A logistic regression model with a dependent variable consisting of two categories is referred to as a binary (dichotomous) logistic regression model. Binary logistic regression is used to analyze the relationship between one dependent variable (Y) and one or more independent variables (X). The dependent variable is dichotomous qualitative data, with a value of 1 indicating the presence of a characteristic and a value of 0 indicating its absence. The form of the logistic regression model is as follows:

$$\pi(x_i) = \frac{\exp(\beta_0 + \beta_1 x_{1i} + \ldots + \beta_p x_{pi})}{1 + \exp(\beta_0 + \beta_1 x_{1i} + \ldots + \beta_p x_{pi})} \quad (1)$$

$$g(x_i) = \ln\left[\frac{\pi(x_i)}{1-\pi(x_i)}\right] = \beta_0 + \beta_1 x_{1i} + \ldots + \beta_p x_{pi} \quad (2)$$

2.5. Classification Model Performance

Classification model evaluation needs to be done to find out how well the model that has been formed is in classifying data. Confusion matrix is a useful tool for analyzing how well the model is in classifying data [14]. The accuracy of the classification model can be measured through the confusion matrix table by comparing the model classification results with the actual classification results. The confusion matrix can be seen in Table 1.

Table 1. Confusion Matrix

Actual	Prediction	
	Positive	**Negative**
Positive	*True Positive (TP)*	*False Negative (FN)*
Negative	*False Positive (FP)*	*True Negative (TN)*

True Positive (TP) is a class that is correctly predicted by the algorithm as positive, while a class that is incorrectly predicted as negative is called False Negative (FN). Meanwhile, a class that is correctly predicted as negative is called True Negative (TN), while a class that is incorrectly predicted as positive is called False Positive (FP). Each parameter of the confusion matrix (TP, TN, FP, and FN) should not be evaluated independently, but in relation to the others.

The performance evaluation metric that is often used in classification based on confusion matrix values is accuracy [15]. Accuracy refers to the precision and strength/effectiveness of the model to provide correct results by comparing the correct prediction value with the entire data.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

3. Research Methodology

3.1. Data

The data used in this study is secondary data obtained from the Central Bureau of Statistics (BPS) in the form of results from the National Socio-Economic Survey (Survei Sosial Ekonomi Nasional, Susenas) conducted in March in Aceh Province in 2022. The data consists of 13,185 observations, with households as the unit of analysis. The variables used in this study amount to 30, consisting of 29 independent variables and one dependent variable, which is the BPNT recipient status, categorized into recipients and non-recipients

3.2. Research Procedure

The data analysis in this study employs descriptive analysis. The data analysis procedure conducted in this research includes the following steps:

a. Data Preparation

Data checking was performed to detect and eliminate incomplete data or data with missing or inconsistent values. Discretization was performed on continuous variables, namely floor area (m^2) and household per capita expenditure (in Rupiah), into discrete ranges or groups as defined by BPS

Indonesia. The categorization of household floor area (m^2) was grouped based on the 2022 housing and settlement statistics [16]. The value ranges for each category of floor area (m^2) are as follows:

Category 1: ≤ 19 m^2 (Very small)
Category 2: 20 – 49 m^2 (Small)
Category 3: 50 – 99 m^2 (Medium)
Category 4: 100 – 149 m^2 (Large)
Category 5: ≥ 150 m^2 (Very large)

The categorization of household per capita expenditure (in Rupiah) was based on the publication of expenditure for consumption by Indonesian residents in March 2021 [17]. The value ranges for each category of household per capita expenditure (in Rupiah) are as follows:

Category 1: < IDR 500,000 per month (Low)
Category 2: IDR 500,000 – IDR 1,000,000 per month (Medium)
Category 3: ≥ IDR 1,000,000 per month (High)

b. Descriptive Analysis

Descriptive analysis was conducted to see the distribution of BPNT recipients in the Aceh Province in the form of a distribution map. Furthermore, to see the accuracy of BPNT distribution in poor areas, a comparison was made using a bar chart between the number of poor people and the number of BPNT recipients in Aceh Province in each Regency/City.

c. Regression Logistic Biner Analysis

To see further what variables affect the status of BPNT recipient households in Aceh Province, logistic regression was conducted. And to identify the characteristics of BPNT recipient households, odds ratio analysis was used. Next, Classification model is formed using binary logistic regression classification to be able to classify households that are recipients and non-recipients of BPNT. The performance of the classification model will be calculated using the accuracy value.

4. Results and Discussion

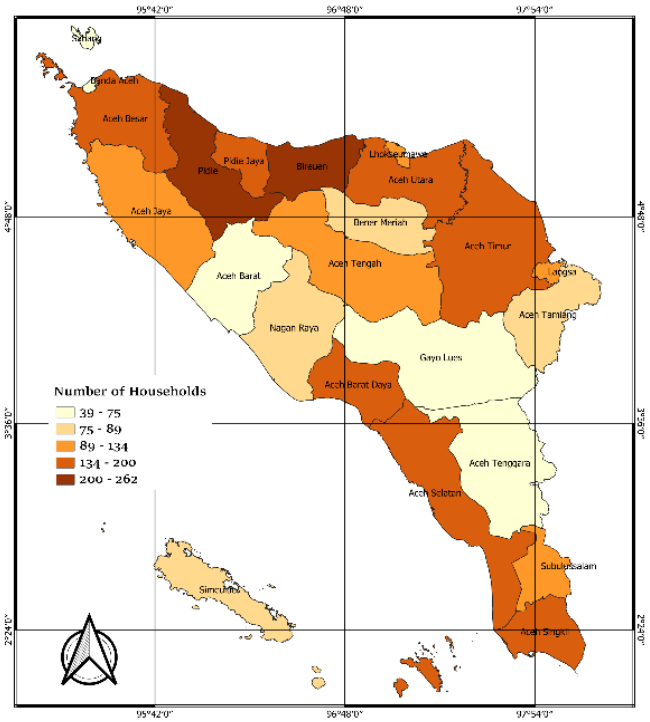
a. Data Preparation

The National Socioeconomic Survey (Susenas) in Aceh Province for 2022 consists of two types of data: household unit data and individual unit data. In this survey, information on both units was collected separately. These two data sets were then merged to create a complete dataset, referred to as data integration. After merging the data, a data check was performed. Once the data was checked and no missing values were found, the continuous independent variables, such as floor area and household per capita expenditure per month, were discretized. The categorization of household floor area (in m^2) was based on the 2022 Housing and Settlement Statistics [16], while the categorization of household per capita expenditure per month

(in Rupiah) was based on the publication of expenditure for consumption by Indonesian residents in March 2021 [17].

b. Descriptive Analysis

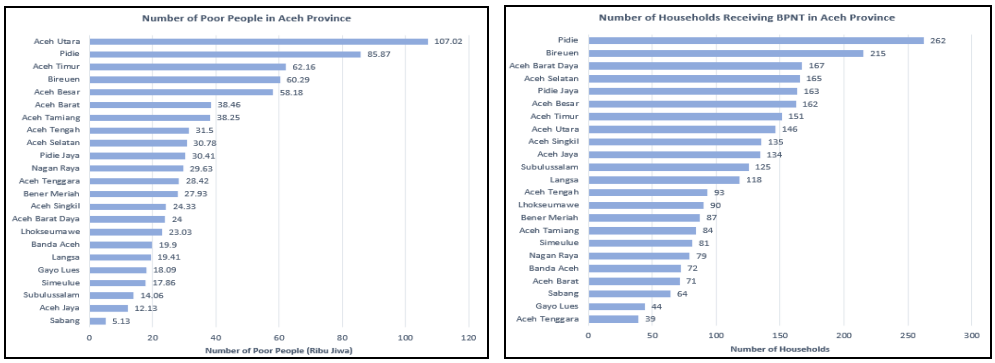
Descriptive analysis was used to describe the characteristics of the research data. The description of BPNT recipient distribution across each regency/city and the description of the characteristics of each variable used in this study are as follows:



Source: ArcGis output (processed, 2024)

Figure 1. Distribution of BPNT Recipient Households in Aceh Province

Figure 1 above explains the distribution of BPNT recipient households in Aceh Province which is symbolized by color gradation. Based on the figure, it can be seen that the darker the color, the more BPNT recipient households in the area. Based on the distribution map, Pidie and Bireun Districts are the areas with the most BPNT recipients in Aceh Province with recipients of 200 - 262 households. Aceh Province is the poorest province in Sumatra. The BPNT program is expected to overcome this poverty by helping poor households meet their food needs. The following is a comparison of data on the number of poor people by Regency/City and BPNT recipients in Aceh Province.



Source: Badan Pusat Statistik Aceh (processed, 2024)

(a) **(b)**

Figure 2. (a) number of poor people in Aceh province (b) number of households receiving BPNT

Based on Figure 2 (a) and (b). It can be seen that Pidie Regency is the district with the largest number of BPNT recipients, namely 262 households. This is not in accordance with the poverty situation (number of poor people) in Pidie Regency which has the second highest number of poor people, namely 85,870 people and a poverty percentage of 18.79% in 2022 in Aceh Province [1]. Supposedly, the largest distribution of BPNT is in North Aceh Regency which has the highest number of poor people in Aceh province at 107.02 people.

The percentage of BPNT recipient households will be observed in five groups: the first group is based on social protection programs, the second is based on the physical condition of the house, the third is based on household activity supports, the fourth is based on household demographic characteristics, and the fifth is based on socioeconomic status and accessibility. This variable grouping is based on each block in the Susenas questionnaire [18].

c. Regression Logistic Biner

To see further what variables influence the status of BPNT recipient households in Aceh Province, logistic regression is used. To identify the characteristics of BPNT recipient households using odds ratio analysis. The following are the results of the logistic regression and odds ratio analysis.

Table 2. Results of Logistic Regression and Odds Ratio

Variable	Coef	*p-value*	Odds Ratio
constant	-1,0972		
Physical Condition of Household			
Type of roof of residence (Others)	0.1571	0.004	1.2101
Type of floor of residence (Wood/Plank)	0.0580	0.000	1.0596
Type of wall of residence (Wood/Plank)	0.0511	0.182	1.0524
Type of toilet of residence (No toilet)	-0.0867	0.010	1.2671
Floor area (Small)	-0.0044	0.000	0.9956
Household Supporting Activities			

Variable	Coef	*p-value*	Odds Ratio
Type of electricity usage (No Electricity)	-0.5842	0.000	1.2671
Cooking fuel (Firewood)	0.0156	0.000	2.0647
Main source of drinking water (Well water)	0.0522	0.027	1.0535
Main source for bathing/washing/other (Well water)	-0.0603	0.171	1.1093
Socio-Economic and Accessibility			
Ownership status of residence (Self-owned)	-0.1274	0.000	5.6649
Household expenditure per capita per month	-0.0918	0.000	1.0000
Refrigerator ownership	0.0570	0.286	1.0367
AC ownership	-0.6819	0.000	0.6092
Computer/laptop ownership	-0.6746	0.000	0.5536
Jewelry ownership (min. 10 g)	-0.3159	0.000	0.7385
Motorcycle ownership	-0.2200	0.001	0.8824
Car ownership	-0.6987	0.000	0.5264
TV ownership (min. 30 inch)	-0.1979	0.007	0.8418
Land/plot ownership	0.0062	0.930	1.0103
Mobile phone ownership	-0.1706	0.003	0.8498
Internet access	-0.4288	0.000	0.6757
Household Head and Family Characteristics			
Last education of household head (Did not finish elementary school)	0.2267	0.000	1.5145
Employment status of household head (Unemployed)	0.0040	0.938	0.9920
Family size (2 members)	0.2758	0.000	1.4711
Number of household members (5 or more members)	0.9193	0.000	5.6149
Number of toddlers (0–4 years old) (2 toddlers)	-0.0082	0.000	1.2505

Source: Phython output (processed, 2024)

Based on Table 2, it can be seen that households that have roof types other than asbestos, zinc, and tiles have a 1.21 times higher chance of receiving BPNT compared to households with asbestos, zinc, and tile roof types. Households with wooden floors and walls have a 1.05 times greater chance of receiving BPNT compared to households with floors and walls other than wood. Households that do not have a toilet have a 1.26 times greater chance of receiving BPNT compared to those with a toilet. And households with a small floor area have a 0.99 times greater chance of receiving BPNT, these results are in line with previous research [19]. Households that do not use electricity have a 1.26 times higher chance of receiving BPNT compared to those that use electricity. Furthermore, households that use firewood as fuel for cooking have a 2.06 times greater chance of receiving BPNT compared to those that use fuel other than firewood. And households that use well water as the main source of water for drinking and other

household activities have a 1.05 and 1.10 times greater chance of receiving BPNT, these results are in line with previous research [20].

Households with per capita monthly expenditure are 1.00 times more likely to be BPNT recipients than those with higher expenditure. Per capita expenditure shows a household's ability to purchase things to meet their needs, the greater the expenditure, the more prosperous the family is. Furthermore, it can also be seen that households that do not have supporting goods such as refrigerators, air conditioners, computers, gold, motorbikes, cars, TVs, cellphones, and land tend to be BPNT recipients compared to households that have these supporting goods, these results are in line with previous research [21].

The variable number of household members has a significant positive effect in the model, meaning that households with ≥5 household members will have a 5.61 times greater chance of receiving BPNT. The results of this study are in line with the results of research conducted by Himi et al. [22] in their research in Bangladesh. The greater the number of household members, the greater the household's need for food. This variable is an indication of the magnitude of the household's burden in meeting daily needs. The variable of the head of the household's working status has a significant and positive effect in this study. It was found that unemployed heads of households were more likely to be BPNT recipients with a tendency of 0.99 times higher than those who were employed. The higher the level of education of the head of the household, the smaller the chance of the household becoming a BPNT recipient. In households whose heads of households do not have a basic education certificate, the tendency to become BPNT recipients is 1.51 times higher than those who have junior high school, high school, diploma and bachelor's degrees [23].

The following are the results of the classification of BPNT recipients and non-recipients using binary logistic regression and data balancing using SMOTE.

Table 3. Confusion Matrix

Actual	Logistic Regression Prediction	
	Non Recipients	Recipients
Non Recipients	5605	2785
Recipients	1725	6665

Source: Phython output (processed, 2024)

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} = \frac{5605+6665}{5605+2785+1725+6665} = 0{,}8083 \qquad (4)$$

In the model accuracy calculation section, the logistic regression classification model demonstrated a satisfactory performance in predicting recipient and non-recipient categories. According to the classification report, the model achieved an accuracy of 80.83%, indicating that it correctly classified data in 80.83% of cases. The confusion matrix provides more detailed information on the model's predictions. Of the total predictions, the model produced 5605 True Negatives (TN), meaning that 5605 "Non-Recipient" samples were accurately

predicted as "Non-Recipients." Additionally, the model generated 6665 True Positives (TP), where 6665 "Recipient" samples were correctly classified as "Recipients." However, there were 2785 False Positives (FP), which represent "Non-Recipient" samples that were incorrectly classified as "Recipients," and 1725 False Negatives (FN), where "Recipient" samples were mistakenly predicted as "Non-Recipients."

Overall, the model demonstrated reasonably good performance with high recall for the "Recipient" class, suggesting that the model is effective in detecting individuals classified as "Recipients." However, the relatively high number of False Positives indicates that the model still struggles with misclassifying "Non-Recipients" as "Recipients." This suggests an opportunity for model improvement, particularly in reducing prediction errors in the "Non-Recipient" class.

These results are in line with previous research [24, 25] which stated that classification using logistic regression and data balancing using SMOTE had more optimal model accuracy results.

5. Conclusion

The study reveals that the BPNT program effectively targets households with economic hardships in Aceh Province, as evidenced by the substantial influence of factors like household size, asset ownership, and basic facilities on eligibility. The logistic regression model used demonstrated a high accuracy rate, affirming the efficacy of BPNT's criteria in identifying those in need. However, the model's false positive rate suggests that additional refinements to eligibility criteria could further optimize the program, especially by minimizing incorrect classifications. To improve BPNT's impact, policymakers should consider additional socio-economic indicators and ensure that data used for eligibility is continuously updated and verified. This approach could enhance program reach, foster equitable distribution, and directly contribute to the Sustainable Development Goal of eradicating hunger and poverty.

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