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Modelling the Prevalence of Stunting in Toddlers Aged 6 – 23 Months in Indonesia with Approaches Multivariate Adaptive Regression Splines and Generalized Additive Model

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ABSTRACT

Stunting remains a major global public health issue, marked by growth failure caused by long-term nutritional deficiencies in early childhood. In Indonesia, stunting prevalence among children under five was reported at 21.5% in 2023. This study employs an analytical observational approach with a cross-sectional design to examine nutritional factors associated with stunting among children aged 6–23 months in Indonesia, using Multivariate Adaptive Regression Splines (MARS) and Generalized Additive Models (GAM). Secondary data were obtained from the 2024 Indonesian Nutritional Status Survey (SSGI), encompassing 36 provinces. Stunting prevalence was defined as the response variable, while predictor variables included the consumption of animal-source protein, sweetened beverages, unhealthy foods, and the lack of fruit and vegetable intake. The analysis began with descriptive statistics and was followed by MARS and GAM modelling. Model performance was assessed using the coefficient of determination (R^2) and Root Mean Square Error (RMSE). The findings indicate that the GAM model outperformed MARS, achieving a higher R^2 0.7734 and a lower RMSE 2.5968, compared to MARS with an R^2 of 0.7319 and an RMSE of 2.8249. While MARS effectively identified structural changes through hinge functions, GAM offered greater modelling flexibility via smooth functions. Among the examined factors, animal-source protein intake showed the strongest association with stunting, followed by the consumption of sweetened beverages and unhealthy foods, whereas inadequate fruit and vegetable intake exhibited a weaker relationship. Overall, both approaches were effective, although GAM demonstrated superior predictive capability for provincial-level stunting analysis.

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A. INTRODUCTION

According to the World Health Organization (WHO), stunting is a condition of impaired growth and development in children resulting from chronic undernutrition, recurrent infections, and an unsupportive environment. It is characterized by a height-for-age measurement that is more than two standard deviations below the median of the healthy child growth standards (WHO, 2006). UNICEF, WHO, and the World Bank (2023) reported that the global prevalence of stunting in 2022 reached 22.3%, equivalent to approximately 148.1 million children worldwide. Asia contributes the largest share, accounting for more than half of the total cases at around 76.6 million children, followed by Africa with approximately 63.1 million children, representing nearly 30% of the global total. The high prevalence of stunting underscores that it remains a serious global public health problem with long-term implications for human capital and development, particularly in developing countries (Victora et al., 2008).

In Indonesia, the prevalence of stunting among children under five declined from 24.4% in 2021 to 21.5% in 2023 according to the Indonesian Nutrition Status Survey (SSGI). However, this still indicates that approximately one in five children experiences stunted growth, underscoring stunting as a persistent public health concern. Stunting reflects chronic undernutrition with long-term consequences for child health and development and is influenced by multifactorial determinants, including inadequate maternal nutrition, insufficient dietary intake, recurrent infections, and poor sanitation and environmental conditions (Schwarzenberg et al., 2018). Children affected by stunting face increased risks of impaired physical growth, heightened susceptibility to infectious diseases, and delayed cognitive and social development, potentially contributing to higher morbidity and mortality at the population level (de Oliveira et al., 2020).

Improving nutritional status is a key component of global development and an essential indicator for achieving the Sustainable Development Goals (SDGs), particularly SDG Target 2.1, which aims to eliminate hunger and ensure access to safe and nutritious food throughout the year (FAO, 2023). Adequate nutrition in early life plays a vital role in preventing stunting and strengthening human capital in developing countries (Victora et al., 2008). In Indonesia, stunting reduction efforts have been reinforced through Presidential Regulation No. 72 of 2021, which promotes integrated nutrition-specific and nutrition-sensitive interventions, exclusive breastfeeding, vitamin A supplementation, and micronutrient provision. Additionally, the Lives Saved Tool (LiST) is utilized to estimate the potential impact of community based interventions on reducing stunting prevalence (Bhutta et al., 2013).

Multivariate Adaptive Regression Splines (MARS) is a non-parametric regression technique designed to flexibly model non-linear associations between response and explanatory variables, while also accommodating interaction effects among predictors (Friedman, 1991). Model selection in MARS is based on identifying the specification that yields the lowest Generalized Cross-Validation (GCV) value (Adiguzel et al., 2023). The GCV criterion is calculated from the residual sum of squares adjusted for model complexity, including the number of basis functions, interaction terms, and sample size (Otok, 2008). In addition, model performance is commonly evaluated using the Mean Squared Error (MSE), which measures the average squared difference between observed and predicted values; smaller MSE values indicate better predictive accuracy (Sabancı & Cengiz, 2022).

Generalized Additive Models (GAM) are the development of general regression models that are non-parametric and flexible in capturing non-linear relationships between dependent variables and independent variables (Hastie & Tibshirani, 1986). Fine function estimation was performed using a smoothing spline with the selection of the fineness level determined through Generalized Cross Validation (GCV). The quality of the GAM model can be assessed using deviance explained which shows how much variation the data is successfully explained by the model, as well as R-Square which describes the proportion of the diversity of response variables described by the predictor variable. The higher the deviance explained and R-Square values, the better the quality of the model produced (Wood, 2016).

Previous studies have demonstrated the effectiveness of both approaches. Rahma (2024) showed that MARS successfully captured non-linear patterns of stunting determinants in Java, while Sutopa and Bari (2018) highlighted the ability of GAM to model complex nutritional relationships in child malnutrition studies. The importance of accounting for non-linear relationships when analyzing stunting and child nutrition outcomes has also been emphasized in broader nutrition studies (Victora et al., 2008). Evidence based evaluations of nutrition interventions further highlight the need for appropriate analytical methods in child nutrition research (Bhutta et al., 2013).

This study aims to analyze nutritional factors related to the incidence of stunting in toddlers aged 6–23 months in Indonesia. The analysis was carried out by applying two modelling approaches, namely Multivariate Adaptive Regression Splines (MARS) and Generalized Additive Model (GAM). Both methods were chosen because they are able to capture complex nonlinear relationships. Furthermore, the results of the MARS and GAM modelling were compared to assess the validity of the model based on two main criteria, namely the determination coefficient (R^2) and the Root Mean Square Error (RMSE).

B. METHODS

This study utilized secondary data derived from the 2024 Indonesian Nutritional Status Survey (*Survei Status Gizi Indonesia*/SSGI), a nationwide survey implemented by the Ministry of Health of the Republic of Indonesia to routinely assess the nutritional conditions of children under five years of age. Data collection in the SSGI is carried out using standardized instruments to obtain information on individual and household characteristics, complemented by anthropometric measurements conducted by trained enumerators in accordance with the WHO Child Growth Standards for identifying stunting.

The analysis covered 36 provinces in Indonesia, with the prevalence of stunting among children aged 6–23 months serving as the dependent variable (Y). Explanatory variables comprised the proportion of animal-source protein consumption (X_1), the proportion of sweetened beverage consumption (X_2), the proportion of unhealthy food consumption (X_3), and the proportion of the population with inadequate fruit and vegetable intake (X_4). The analytical process began with descriptive statistics to summarize the distribution and characteristics of all study variables.

Furthermore, non-parametric regression techniques, specifically Multivariate Adaptive Regression Splines (MARS) and Generalized Additive Models (GAM), were employed. The MARS approach was applied to identify non-linear patterns and interaction effects using hinge-based basis functions, whereas GAM captured non-linear relationships through smooth functions for each covariate. Model evaluation was conducted by directly comparing predicted outcomes with observed values using the full provincial-level dataset, without the application of cross-validation procedures. Model performance was assessed using the Root Mean Square Error (RMSE) and the coefficient of determination (R^2) to identify the most appropriate model for explaining variations in stunting prevalence across Indonesia.

C. RESULT AND DISCUSSION

1. Descriptive Statistics

Descriptive statistics are used in quantitative research to summarize and describe sample data using measures of central tendency, dispersion, and graphical presentation, without involving population-level inference (Harbison & Simmons, 2024). Table 1 presents the results of the descriptive statistical analysis of stunting prevalence in Indonesia and its associated variables.

Table 1. Variable Characteristics

Variables	N	Mean	Minimum	Maximum
Y	36	21,97	8,60	37,00
X_1	36	77,11	55,20	88,10
X_2	36	14,37	3,30	30,10
X_3	36	38,12	17,50	62,00
X_4	36	28,23	13,20	57,40

Based on the results of descriptive statistical analysis, it is known that the prevalence of stunting (Y) in Indonesia ranges from 8.6% to 37%, with an average of 21.97%. This figure shows that the problem of stunting in children under five in Indonesia is still relatively high and requires attention and continuous nutritional interventions. For the variable consumption of animal protein sources (X_1), the lowest value was recorded at 55.2% in South Papua Province, while the highest value reached 88.1% in the Special Region of Yogyakarta Province, with an average of 77.11%. This condition indicates that most of the children under five in Indonesia have obtained a fairly good intake of animal protein, although there are still differences between provinces.

Furthermore, the consumption of sugary drinks (X_2) has an average of 14.37%, with a range of 3.3% in the Bangka Belitung Islands Province to 30.1% in East Nusa Tenggara Province. This fairly wide variation shows that there are differences in consumption patterns of sugary drinks between regions. The proportion of toddlers who often consume sugary drinks has a higher potential to experience health problems and growth disorders.

Meanwhile, the consumption of unhealthy food (X_3) showed an average of 38.12%, with a minimum value of 17.5% in North Sulawesi Province and a maximum of 62% in Banten Province. These findings show that the consumption of unhealthy foods among toddlers is still quite high, which can have a negative impact on nutritional quality and health status of children. The proportion of toddlers who do not consume fruits and vegetables (X_4) has an average of 28.23%, with a range of 13.2% in Bengkulu Province to 57.4% in North Maluku Province. This condition shows that the consumption habits of fruits and vegetables in toddlers are still low in some provinces, so it can reduce the intake of essential vitamins and minerals needed to support optimal growth.

2. MARS Modelling

The selection of the optimal Multivariate Adaptive Regression Splines (MARS) model is primarily guided by the Generalized Cross-Validation (GCV) criterion, where lower GCV values indicate a more favorable trade-off between model accuracy and complexity. In addition, the coefficient of determination (R^2) is used to evaluate model fit by quantifying the proportion of variation in the response variable that is explained by the set of predictor variables. Higher R^2 values indicate stronger explanatory power of the model in capturing the relationship between predictors and the response variable (Abed et al., 2023).

In this study, the MARS modelling produced a GCV value of 14.186 and an R^2 of 0.732. The GCV value serves as an internal measure to control model complexity and reduce the risk of overfitting, while the R^2 result suggests that approximately 73.2% of the variation in the response variable can be explained by the predictors included in the model. Based on these results, the MARS modelling formed is as follows:

$$\hat{y} = 24{,}7789 - 1{,}6058 \cdot h(X_1 - 74{,}8) + 5{,}0018 \cdot h(X_1 - 79{,}9) - 5{,}4170 \cdot h(X_1 - 82{,}4) + 0{,}6914 \cdot h(X_2 - 17{,}3) \quad (1)$$

with,

$$h(x - c) = \max(0, x - c) \quad (2)$$

The results of the MARS modelling on equation (1) show that of the four predictor variables, only the consumption of animal protein (X_1) and consumption of sugary drinks (X_2) were included in the model. The variables of unhealthy food consumption (X_3) and not eating fruits and vegetables (X_4) were not selected, so their contribution to the prevalence of stunting was relatively small compared to the variables X_1 and X_2. The intercept value of 24.7789 illustrates the prevalence of stunting when the entire effect of X_1 and X_2 is below the relevant node point. In other words, without considering changes in predictive variables, the prevalence of early stunting is estimated to be around 24,7789%.

At h(X_1 – 74.8) with a coefficient of -1.6058. This means that when the consumption of animal protein (X_1) exceeds 74.8%, the prevalence of stunting begins to decrease with *a slope* of -1.6058. This is consistent with the nutritional theory that increased consumption of animal protein is related to improved nutritional status and reduced stunting (Asare, et al., 2022). At h(X_1 – 79.9) with a coefficient of 5.0018. After the X_1 variable passes the 79.9% point, there is a change in pattern, namely an increase in stunting with a slope of +5.0018. This can indicate the presence of complex factors, such as provinces with high animal protein consumption having dietary imbalances.

Furthermore, at h(X_1 – 82.4) with a coefficient of -5.417, when the consumption of animal protein exceeded 82.4%, the pattern changed again, namely stunting decreased significantly with *a slope* of -5.417. This illustrates that at very high levels of consumtion, animal protein again provides clear benefits for reducing stunting. Thus, X_1 relationship to stunting is not linear, but *piecewise* non-linear. Finally, h(X_2 – 17.3) with a coefficient of +0.6914 with the variable consumption of sugary drinks, when the value of X_2 passed 17.3%, the prevalence of stunting increased with *a slope* of +0.6914. These findings indicate that the high consumption of sugary drinks at the provincial level is associated with an increase in the prevalence of stunting, and is in line with previous research findings that suggest that consumption of sugary drinks can negatively impact children's nutritional status (Brown et al., 2024). To understand how the MARS model captures the relationship between predictor variables and stunting prevalence, a graph of the modelling results is shown. This graph shows the form of a piecewise function that is built through the hinge function base, so that non-linear patterns and points of change in relationships between variables can be visually observed, as shown in Figure 1.

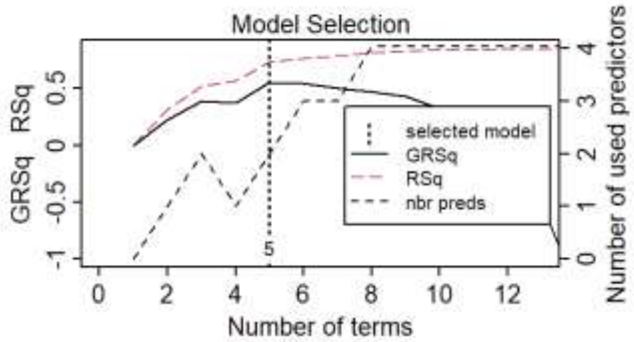

Figure 1. MARS Result Plot Selection Model

Based on Figure 1 the results of Multivariate Adaptive Regression Splines (MARS) modelling, the best model with 5 terms involving 2 of the 4 predictor variables, namely X_1 and X_2, was obtained. The variables X_3 and X_4 are not used because they do not make a significant contribution to model formation. An R-Square value of 0.7319 indicates that the model is able to account for 73.19% variation of response variables. The Generalized R-Square (GRSq) value of 0.5494 indicates that the model has a fairly good generalization ability. The selection of a model with 5 terms is considered optimal because it is able to maintain a balance between accuracy and complexity of the model. Thus, the MARS model obtained can be considered representative in explaining the relationship between the response variable and the predictor variable used, as shown in Figure 2.

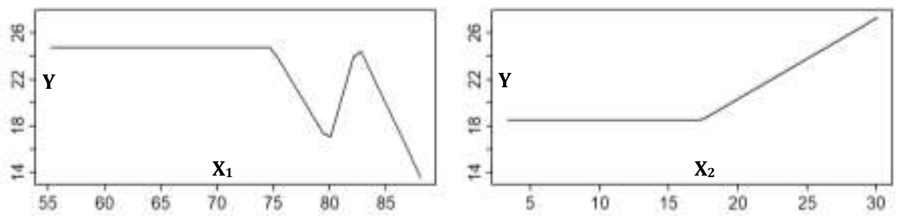

Figure 2. Partial Dependence Plot of MARS Results Variables X_1 and X_2

Based on Figure 2, the variable X_1 has a non-linear influence on the response variable. The Y value is relatively stable when $X1 \leq 74.8$, then decreases at intervals of 74.8–79.9, increases again in the range of 79.9–82.4, and decreases after passing 82.4. This shows that X1 plays a major role in the value range of 75–85. Meanwhile, the influence of X_2 is simpler, i.e. it has no effect on Y until the value of 17.3, but after passing this point, the increase in X_2 will cause a linear increase in Y. Thus, the MARS model confirms that X_1 and X_2 are significant predictors, with X_1 providing complex non-linear effects and X_2 providing linear effects after a certain threshold.

3. GAM Modelling

In the Generalized Additive Model (GAM) framework, model evaluation is based on the proportion of deviance explained and the coefficient of determination (R^2). The deviance explained metric reflects the model's ability to capture variability in the observed data, while R^2 represents the proportion of variation in the response variable accounted for by the predictor variables. Higher values of both indicators suggest improved model performance (Pedersen et al., 2019). The GAM results show a deviance explained of 77.3% and an R^2 value of 0.687. These findings indicate that the model explains approximately 68.7% of the variability in the response variable, suggesting that the overall model performance can be considered satisfactory. Based on these results, the GAM modelling formed is as follows:

$$Y \sim s(X_1) + s(X_2) + s(X_3) + s(X_4) \tag{3}$$

The results of the GAM modelling show that the intercept value is 21.9667. This means that the average value of stunting prevalence when all predictor variables are in a state of zero due to *the smooth* effect and without considering the non-linear effect of the variables X_1 to X_4, is 21.9667%. This value is the starting point for estimation before the influence of predictor variables is incorporated into the model. Furthermore, the non-linear effects of each predictor variable are captured through *smooth terms*. Based on the results of GAM modelling on the variable of animal protein consumption (X_1), the value of effective degrees of freedom (*edf*) shows a very high number of 6.664 with *a p-value* of 0.000286 (*p-value* < 0.001). This indicates a significant nonlinear relationship. This pattern shows that at some levels of animal protein consumption, the prevalence of stunting tends to decrease, while at other levels it actually increases. In other words, the influence of animal protein on stunting is not always unidirectional, but varies according to the intensity of consumption.

In the sugary beverage consumption variable (X_2), the edf value is 1 with *a p-value* of 0.000420 (*p-value* < 0.001) indicating that the influence of X_2 is linear and significant. This means that the higher the consumption of sugary drinks, the higher the prevalence of stunting. This can be explained because excess sugar intake often replaces nutritious foods, so the quality of daily intake of toddlers decreases. Then, the variable of unhealthy food consumption (X_3) also has edf = 1 with *a p-value* of 0.011476 (*p-value* < 0.05) This shows that the variable X_3 is also linear and significant. Unhealthy food consumption patterns contribute to the increased prevalence of stunting. Although the effect is not as large as X_1 and X_2.

In the variable of not consuming vegetables and fruits X_4, it had *an edf* value of 1 with *a p-value* of 0.667041 (*p-value* > 0.001) which shows that this variable is linear but not significant in the model. Thus, its contribution to the variation in stunting prevalence is relatively small after considering the effects of other variables. This is in line with the findings of WHO (2020) which states that fruit and vegetable consumption has a positive relationship with health, but the impact is often influenced by other nutritional intake factors that are more dominant (Angelino et al., 2019). The pattern of relationships between variables is also visualized through graphs of GAM modelling results. This graph displays the smooth functions of each predictor, so that the form of linear and non-linear relationships can look more flexible and continuous.

Thus, the interpretation of the contribution of each variable in influencing stunting prevalence can be carried out more comprehensively, as shown in Figure 3.

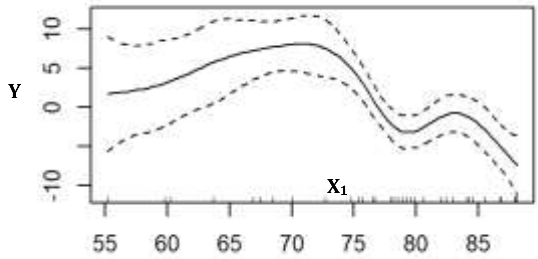

Figure 3. Smooth Function Plot of Animal Protein Consumption Variable (X_1) on Stunting Prevalence (Y) Based on GAM Model

In Figure 3 it can be seen that the variable X_1 has a fairly complex non-linear pattern. The graph shows that in the low X_1 range to about 70, the effect tends to increase, but after crossing the threshold of 75–80 there is a sharp to negative decrease. After that, the curve fluctuates again. This shows that the consumption of animal protein does not necessarily reduce the prevalence of stunting, but there is an optimal point, and if a certain threshold is crossed, it can change direction, as shown in Figure 4.

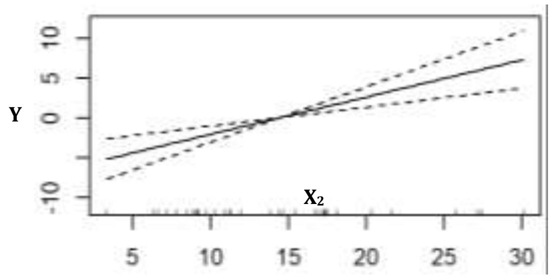

Figure 4. Smooth Function Plot of Sugary Beverage Consumption Variables (X_2) on Stunting Prevalence (Y) Based on GAM Model

In Figure 4 it can be seen that the variable X_2 has a significant linear pattern. The higher the consumption of sugary drinks, the prevalence of stunting is also increasing consistently. This illustrates that the consumption of sugary drinks plays a role as a risk factor that worsens the condition of stunting.

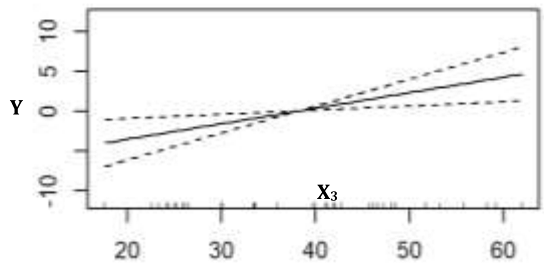

Figure 5. *Smooth Function Plot* of Unhealthy Food Consumption Variables (X_3) to Stunting Prevalence (Y) Based on GAM Model

In Figure 5 it can be seen that the X_3 variable also shows a significant linear pattern. Based on a low X_3 value, it can have a small effect on stunting, but as the consumption of unhealthy foods increases, the prevalence of stunting increases. This pattern confirms that unhealthy foods contribute to increasing the risk of stunting, although the effect is not as strong as other variables.

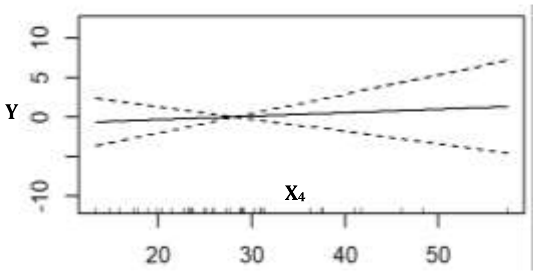

Figure 6. Smooth Function Plot of Variable Non-Consumption of Fruits and Vegetables (X_4) on Stunting Prevalence (Y) Based on GAM Model

In Figure 6 the X_4 variable looks a relatively flat graph with no clear patterns. This shows that not eating fruits and vegetables does not have a significant effect on the prevalence of stunting. In other words, these variables do not contribute significantly to the model.

4. Comparison of MARS and GAM

Based on the calculation results, Multivariate Adaptive Regression Splines (MARS) modelling yielded an R^2 value of 0.7319 with an RMSE of 2.8249. This R^2 value shows that about 73.19% of the variation in stunting prevalence can be explained by the MARS model, while the rest is explained by other factors outside the model. The relatively small RMSE value indicates that the model's prediction error is still quite low. In the Generalized Additive Model (GAM) modelling, the R^2 value was 0.7734 with an RMSE of 2.5968. This R^2 value is higher than MARS which means that GAM is able to explain around 77.34% of the variation in stunting prevalence, thus providing better predictive ability. In addition, the lower RMSE GAM value compared to MARS indicates that the GAM model has a higher prediction accuracy (Teng et al., 2023).

Based on the results of the MARS and GAM graphs, it can be seen that the two methods have different abilities in capturing the pattern of relationship between nutritional factors and stunting prevalence. MARS emphasizes the formation of *piecewise* functions through the base of *hinge* functions, resulting in models that can capture changes in patterns sharply at certain points. This is evident in the role of the variable X_1, where the relationship with stunting is fluctuating and non-linear. Meanwhile, GAM uses a smooth-function approach that is more flexible in describing non-linear and linear relationships simultaneously. Visualization of *the smooth* curve in GAM shows that X_1 has a complex non-linear relationship pattern, while X_2 and X_3 are more likely to be linear, and X_4 is relatively insignificant. Both models provide complementary results, where MARS is able to show points of change explicitly, while GAM shows a more subtle shape of the relationship curve (Valavi, et al., 2022).

D. CONCLUSION AND SUGGESTIONS

This study aimed to analyze nutritional factors associated with stunting prevalence among children aged 6–23 months in Indonesia and to compare the performance of MARS and GAM in modelling these relationships. The results indicate that animal-source protein consumption, sweetened beverage consumption, and unhealthy food consumption significantly influence variations in provincial-level stunting prevalence. The relationship between animal-source protein consumption and stunting exhibits a non-linear pattern, while sweetened beverage and unhealthy food consumption tend to show linear and significant associations. In contrast, the variable representing non-consumption of fruits and vegetables does not contribute significantly to explaining stunting prevalence at the provincial level.

In line with the methodological objective of this study, the comparative analysis demonstrates that the Generalized Additive Model (GAM) outperforms the Multivariate Adaptive Regression Splines (MARS) in modelling nutritional determinants of stunting at the provincial level. This finding highlights the scientific and methodological contribution of the study, indicating that GAM provides a more robust and flexible framework for capturing non-linear relationships in aggregated nutritional survey data, and therefore represents a more appropriate modelling approach for analyzing stunting using national-level survey data.

There are several suggestions related to the sustainability of this research. First, nutritional interventions need to be directed at increasing the consumption of animal protein in a balanced amount, although it plays an important role, but excessive protein consumption can actually have the opposite effect. Second, the consumption of sugary drinks and unhealthy foods needs to be reduced because it consistently increases the prevalence of stunting. For further research, it is recommended to use a larger sample taking into account additional variables such as economic, parenting, and environmental factors, and can be compared with other methods that are more comprehensive and accurate.

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