SAINSTEK: JURNAL SAINS DAN TEKNOLOGI
Publisher: Universitas Islam Negeri Mahmud Yunus Batusangkar
Website: https://ejournal.uinmybatusangkar.ac.id/ojs/index.php/sainstek
E-mail: sainstek@uinmybatusangkar.ac.id

June 2025
Vol 17 No 1
ISSN: 2085-8019 (p)
ISSN: 2580-278x (e)
pp : 15-24

Multivariate Adaptive Regression Splines for Contraceptive Use

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Article History
Received: 14 June 2025
Reviewed: 20 June 2025
Accepted: 26 June 2025
Published: 30 June 2025

Key Words
Contraceptive use; Socio-economics factors; Multivariate Adaptive Regression Spline (MARS);Non-linear modeling.

Abstract
Contraception is a critical public health issue, particularly in countries with high birth rates. In Indonesia, family planning has long been a priority, but challenges remain, especially in regions like West Sumatra, where socio-cultural factors influence contraceptive use. This study investigates the factors affecting contraceptive use in West Sumatra, focusing on socio-economic, cultural, and demographic variables. Traditional linear models often fail to capture the non-linear relationships and interactions between variables. To address this, the study employs the Multivariate Adaptive Regression Splines (MARS) method, a non-parametric regression technique that adapts to non-linearities and interactions. The model incorporates variables such as age, education, income, and access to family planning services, and identifies critical points (knots) where significant changes in contraceptive use occur. Results show that socio-economic factors, particularly education, income, and access to healthcare, significantly influence contraceptive use. The model demonstrates strong predictive performance, with an R^2 value of 0.98, indicating it explains 98% of the variability in contraceptive use patterns. By identifying key factors and their interactions, this study offers valuable insights for policymakers and public health officials, suggesting that improving access to services and addressing socio-cultural barriers can enhance family planning participation. The flexibility and predictive accuracy of the MARS model make it a valuable tool for evidence-based family planning interventions in West Sumatra and similar regions.

INTRODUCTION

Birth control is an important public health issue, especially in countries with high birth rates (Tumlinson et al., 2015; Chandra-Mouli & Akwara, 2020). One important effort in managing population growth is through the use of contraception, which not only has an impact on reducing birth rates but also improves the quality of maternal and child health, supporting economic development (Guilkey & Speizer, 2022; Karim et al., 2024). In Indonesia, family planning has long been a national priority, but its implementation faces various obstacles, especially in areas with unique social, cultural and demographic characteristics such as West Sumatra (Rati Sumanti et al., 2022).

West Sumatra has a socio-cultural context influenced by traditional Minangkabau values and a strong religion. These factors often influence people's behavior in choosing and using contraceptive methods (Kismiasih Adethia et al., 2024; Nasir, 2020; Wilisandi & Feriani, 2020). In addition, access to health services, education level, family income and reproductive age also influence couples' decision to use contraception (Palamuleni, 2013; Handayani, 2010). Building on these established factors, this study aims to develop a predictive model that captures both individual socioeconomic characteristics and their interactive effects on family planning decisions, with particular attention to threshold effects in underserved populations.

The relationship between these factors is often complex and non-linear, making it difficult to model with traditional analytical approaches. Previous studies on contraceptive use have mostly tended to use conventional statistical methods such as linear o regression (Michael et al., 2024; Azanaw et al., 2022), which assume a linear relationship between predictor variables and contraceptive use rates. However, the relationships between variables such as age, number of children, education, and contraceptive method preference are often non-linear and involve interactions between variables. As a result, the results of analyses using these conventional methods are often inaccurate in representing the actual patterns in the community.

The Multivariate Adaptive Regression Splines (MARS) approach offers a solution to overcome this challenge. MARS is a non-parametric regression method that can adaptively capture non-linear relationships and interactions between variables. By using spline basis functions, MARS is able to build flexible models to predict contraceptive use rates based on demographic, social, and economic factors. In addition, MARS allows the identification of critical points (knots) where significant changes occur, such as a certain age or education level that affects contraceptive use decisions. Extensive academic investigations have been dedicated to examining the key factors influencing the MARS model. In particular, Poisson regression has been employed to enhance the MARS model (Prihastuti Yasmirullah et al., 2021), while bootstrap aggregating of multivariate adaptive regression splines has been applied in observational studies on diabetic cases (Otok et al., 2020). Furthermore, the identification of causative factors for hemorrhagic fever has been explored by (Sriningsih et al., 2021, 2023; Yasmirullah et al., 2021), taking into account both continuous and categorical responses. The process of ANOVA decomposition and variable importance analysis within the context of MARS is outlined in (Otok et al., 2023). Additionally, research has been focused on estimating hourly global solar radiation in Hong Kong through the application of the MARS technique (Li et al., 2019). Parameter estimation of spatial error models using multivariate adaptive generalized Poisson regression splines is discussed in (Yasmirullah, Otok, Purnomo, et al., 2023), while a hybrid model combining spatial autoregressive methods with multivariate adaptive generalized Poisson regression splines is presented in (Yasmirullah, Otok, Trijoyo Purnomo, et al., 2023). Furthermore, the determination of factors influencing stunting and wasting has been addressed using both Fuzzy C-Means (FCM) and MARS approaches (Meilisa et al., 2023a, 2024). The factors influencing dengue fever have also been identified through the MARS method (Meilisa et al., 2023b).

The application of MARS in this study aims to provide new insights into patterns of contraceptive use in West Sumatra, focusing on the influence of interactions between variables such as education, income, and access to health services. With a more accurate and flexible model, it is expected that this analysis can provide more in-depth information to support more effective and evidence-based policy making. The findings of this study can be generalized to other regions with similar demographic and socioeconomic characteristics, thereby strengthening family planning programs and contributing to improved quality of life at the national level.

METHOD

Multivariate Adaptive Regression Splines (MARS)

This research is an applied research with a quantitative review, by taking the necessary data then conduct an analysis with Multivariate Adaptive Regression Splines (MARS) to determine the factors that influence contraceptive use in West Sumatra. The MARS model is a flexible method for nonlinear regression that uses a mix of truncated splines and recursive partitioning regression. It captures complex relationships by using piecewise linear basis functions, allowing for the adaptive modelling of interactions between predictor variables (Friedman, 1991) . We formulate the model as follows:

$$\begin{aligned} y_i &= f\left(x_{1i}, x_{2i}, \ldots, x_{pi}\right) + \varepsilon_i; i = 1,2,\ldots,n \\ &= \alpha_0 + \sum_{m=1}^{M} \alpha_m \prod_{k=1}^{K_m} \left[s_{km}\left(x_{v(k,m)i} - t_{km}\right)\right]_+ + \varepsilon_i \\ &= \alpha_0 + \sum_{m=1}^{M} \alpha_m B_{mi}(\mathbf{x}, \mathbf{t}) + \varepsilon_i \end{aligned} \tag{1}$$

In this model, the response variable y_i for the i-th observation is modeled as

$$y_i = f(x_i) + \varepsilon_i \tag{2}$$

Where :

$x_i = (x_{i1}, x_{i2}, \ldots, x_{ip})$ is a vector of predictor variables for the $i-th$ observation. $f(x_i)$ is a function relating the predictors to the response and ε_i is the error for the $i-th$ observation.

The model captures complex relationships between the response variable and predictors through piecewise linear basis functions. The first part of the equation represents a general nonlinear function, while the second part expresses the model as a sum of products of these basis functions, $s_{km}\left(x_{v(k,m)i} - t_{km}\right)$, where t_{km} are the knots that determine where the piecewise linear functions change. Each basis function is associated with a coefficient α_m and the sum of all basis functions gives the overall predicted response. The model is flexible, allowing for various degrees of interaction between predictors by adjusting the number of basis functions and knots. The final form of the model combines the coefficients and basis functions, providing a highly adaptable approach to regression that can effectively capture nonlinear relationships in the data. This methodology is widely used for regression problems with complex structures, as it automatically adjusts to changes in the data by using the basis functions to fit piecewise linear segments.

Contraception

Contraception is a crucial step in family planning, helping to reduce unwanted pregnancies and improve maternity and child health. The use of contraception is influenced by various factors, including age, education, employment status, poverty, and access to healthcare services. According to the World Health Organization (Organization, n.d.), over 200 million women in developing countries still face challenges in accessing safe and effective contraception, leading to high rates of unintended pregnancies (Nations, 2022).

Education plays a significant role in increasing contraceptive use. In many developing countries, women with lower education levels tend to have limited knowledge about contraceptive methods. On the other hand, in countries with higher levels of education, such as in Europe and North America, the use of contraception is higher due to increased access and awareness of its importance for reproductive health (Amanda et al., 2025).

Poverty is also a major barrier to contraceptive use. In countries with high levels of poverty, such as in Sub-Saharan Africa and South Asia, women often cannot access family planning services due to financial constraints. The United Nations Population Fund (Cleland et al., 2014) states that improving access to contraception can reduce unintended pregnancies and contribute to long-term poverty reduction.

Dataset and Research Variables

The data used is obtained from the publication of the BPS-Statistics Indonesia through the website sumbar.bps.go.id and the publication of the Family Planning Coordinating Board (BKKBN) of West Sumatra province through the SIGA website, the related variables that will be used is the data in contraceptive use in 2023. data. The independent variables used are age of active participant: number of participant under 30 years (X1), number of participant overs 30 years (X2), average years of schooling (X3), proportion of working women over the age of 15 (X4), proportion of productive age women with education below junior high school (X5), proportion of poor people (X6), access to family planning information services (X7). while the dependent variable is the number of active family planning participants (Y).

The analysis steps carried out in this study are as follows: 1) Making descriptive statistics and data plots of the dependent variable with each independent variable. 2) Plot between the dependent variable and each independent variable. 3) Specify the maximum number of Basis Functions (BF), typically set at 2 to 4 times the number of independent variables. The independent variables used in this study were 4 variables, so the maximum basis function formed are 8, 12, and 16. 4) Determine the maximum number of interactions (MI), namely 1, 2, and 3 interactions. If MI <3 then it will cause a very complex model interpretation. 5) Determine the best model by looking at the Generalized Cross Validation (GCV) value. The smaller the GCV value, the better the model is compared to other models. 6) Obtain variables that have a significant effect on the formation of the MARS model. 7) Interpret the results.

RESULT AND DISCUSSION

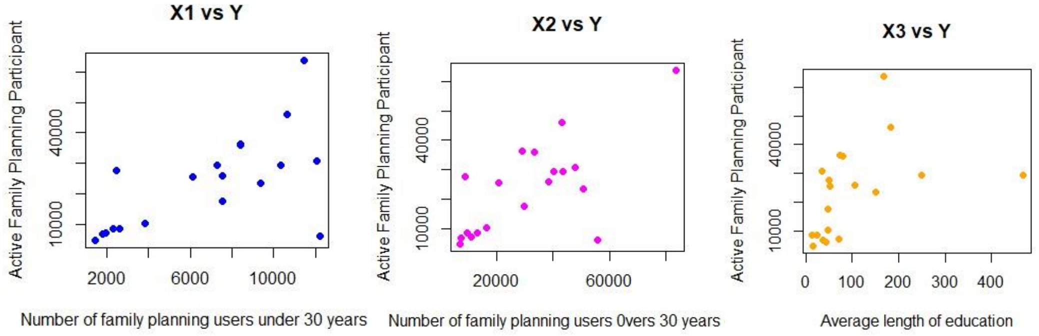
Characteristic of Data

This study uses a number of variables that reflect the demographic, social, economic, and accessibility aspects that influence the level of participation in the family planning programme. The description of data on each variable observed in this study can be seen in the following table:

Table 1. Description of Variables

Variables	Mean	Min.	Max.
Age of active participants			
< 30 years	6.738	1.449	12.192
> 30 years	30.970	6.858	83.431
Average years of schooling	100.79	13	467
Family Planning service clinics	70.91	65	75
Proportion WUS with education below junior high school	51.93	29.65	70.14
Proportion of poor population	47.58	30.17	68.81
Access to family planning information services	17.92	3.81	40.44

The following scatter plot is used to illustrate the pattern of relationship between the independent and dependent variables.



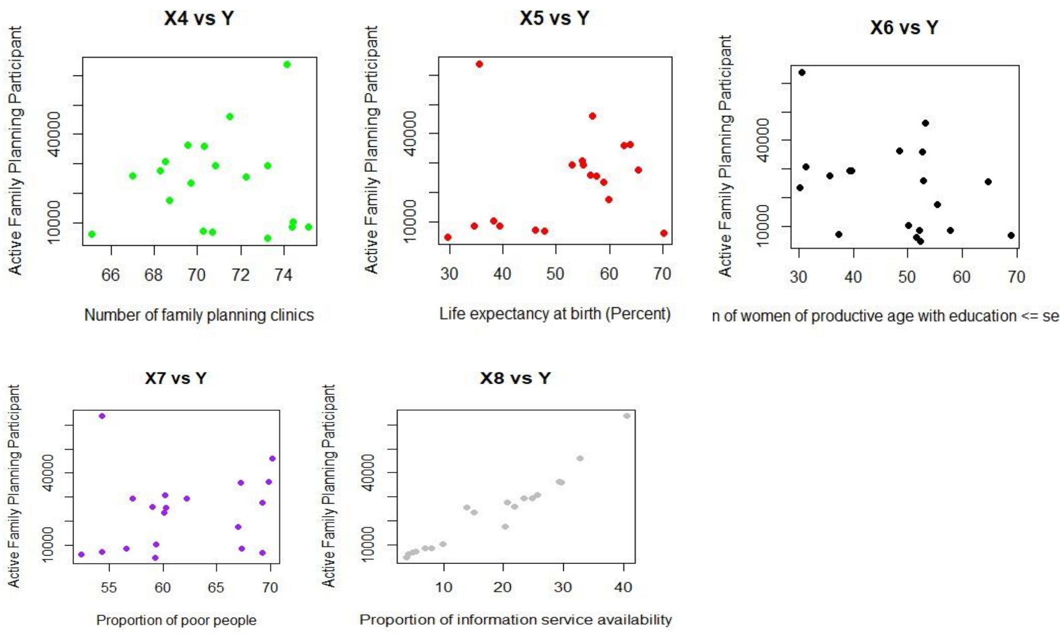


Figure 1. Scatter plots illustrating the response variable y to the predictor variable x

Based on this visualization, it appears that the relationship between the variables tends not to show a clear pattern, so further analysis is required to understand the nature of this relationship, especially with approaches that are able to capture non-linear patterns, such as Multivariate Adaptive Regression Splines (MARS).

Estimation Procedure

Parameter estimation for the contraception model by selecting the optimal MARS configuration based on the lowest Generalized Cross-Validation (GCV) value. The basic function (BF) was defined for each region, with typical BF values ranging from two to four times the number of predictor variables. In this study, six predictor variables were considered to influence contraception use, leading to the evaluation of 12, 18, and 24 BF combinations. The maximum interaction (MI) represents the number of variables that can interact within the model. We tested MI values of 1, 2, and 3, where MI = 1 allows interaction of a single variable, MI = 2 permits interaction between two variables, and MI = 3 allows up to three variables to interact. The minimum observation (MO) defines the number of observations between knots, with values of 1, 2, and 3 used in this analysis, as GCV tends to increase when MO exceeds this range, as illustrated in the Table 2.

Table 2. Integration of Pruning MARS in the Contraception Model.

Basis Func.	Max Inter	Min Observ	Nilai GCV	R^2
12	1	1	2544672.25	0.9839
12	1	2	1816954.41	0.9885
12	1	3	1678959.80	0.9894
12	2	1	2438214.80	0.9846
12	2	2	1529137.10	0.9903
12	2	3	1591766.51	0.9900

Basis Func.	Max Inter	Min Observ	Nilai GCV	R^2
12	3	1	2271324.24	0.9857
12	3	2	1529137.10	0.9903
12	3	3	1591766.51	0.9900
18	1	1	156956.07	0.9990
18	1	2	171200.69	0.9989
18	1	3	151627.68	0.9990
18	**2**	**1**	**1031.94**	**1.0000**
18	2	2	26554.38	0.9998
18	2	3	279050.91	0.9982
18	3	1	110061.65	0.9993
18	3	2	26554.38	0.9998
18	3	3	279050.91	0.9982
24	1	1	156956.07	0.9990
24	1	2	171200.69	0.9989
24	1	3	151627.68	0.9990
24	2	1	1031.94	1.0000
24	2	2	26554.38	0.9998
24	2	3	38284.61	0.9998
24	3	1	110061.65	0.9993
24	3	2	26554.38	0.9998
24	3	3	32489.64	0.9998

The table summarizes the model performance across various configurations, including different numbers of basis functions, maximum interactions, and minimum observations. Notably, as the number of basis functions and interactions increases, the Generalized Cross-Validation (GCV) values tend to decrease, indicating improved model fit. The lowest GCV value, 1,031.94, is observed for the configuration with 18 basis functions, 2 interactions, and 1 minimum observation. Furthermore, the R^2 values consistently remain close to 1, with the highest R^2 value of 0.99999, indicating near-perfect model accuracy and stability. These results highlight that increasing model complexity enhances predictive performance, with the stability of the model being maintained across configurations. The best MARS model is indicated by the following equation, which represents the optimal configuration based on the lowest Generalized Cross-Validation (GCV) value, demonstrating the best model performance in terms of accuracy and stability.

$$\hat{y} = 27254.5904 - 0.1585BF1 - 0.4423BF2 + 0.0556BF3 - 0.0087BF4 - 63.1448BF5 + 335BF6 - 127.6501BF7 - 11.3956BF8 - 0.0339BF9 + 0.0546BF10 - 0.0005BF11 + 0.0004BF12 - 00012BF13 + 0.0002BF14 + 0.0272BF15 + 0.2502BF16 \quad (2)$$

With,

$$BF1 = h(65574 - X1); BF2 = h(X1 - 65574);$$
$$BF3 = h(1.15941e+06 - X2); BF4 = h(X2 - 1.15941e+06);$$
$$BF5 = h(231 - X4); BF6 = h(X4 - 231); BF7 = h(2273.3 - X6);$$
$$BF8 = h(X6 - 2273.3); BF9 = h(65574 - X1) * h(X5 - 70.84);$$
$$BF10 = h(65574 - X1) * h(70.84 - X5);$$
$$BF11 = h(10933 - X1) * h(X6 - 2273.3);$$
$$BF12 = h(X1 - 10933) * h(X6 - 2273.3);$$
$$BF13 = h(X2 - 1.15941e+06) * h(X4 - 187);$$
$$BF14 = h(X2 - 1.15941e+06) * h(187 - X4);$$
$$BF15 = h(231 - X4) * h(X6 - 2525);$$
$$BF16 = h(231 - X4) * h(2525 - X6)$$

This model utilizes basis functions (BF1 to BF16) constructed from transformations of input variables $X1$ to $X6$, including interactions between variables. These basis functions enable the model to capture non-linear relationships that cannot be explained by traditional linear models. The knot values, such as those influencing $X1$ at 65574, serve as points where the behavior of the basis function changes. When the value of $X1$ crosses this knot, the shape of the corresponding basis function changes, allowing the model to adapt to the changing patterns in the data around this point. Interactions between variables, such as in $BF10 = h(65574 - X1) * h(70.84 - X5)$, are critical in the model. This basis function will contribute meaningfully to the model only under the following conditions:

1. The value of $X1$ must be less than 65574.
2. The value of $X5$ must be less than 70.84.

In other words, BF10 becomes active only when both $X1$ and $X5$ are below their respective knot values, indicating that the interaction between $X1$ and $X5$ influences the prediction $\hat{y}$ only when these conditions are met. This allows the model to capture specific effects that are relevant only within certain ranges of the input variables. The use of basis functions and the placement of knots provide the model with greater flexibility, enabling it to capture complex relationships between the predictors and the dependent variable, as well as the interactions between variables that may have a significant impact on the predictions, depending on the values of the input variables. In this model, Basis Function 10 (BF10), activation of this function occurs only when both the number of participants aged over 30 (X2) and the average years of schooling (X3) are below their respective knot values—for example, X2 < 65,574 and X3 < 70.84. This implies that the interaction between age and education influences family planning participation only within specific thresholds. In this case, when both older participation is relatively low and education is below a certain level, these conditions jointly contribute to a distinctive effect on contraceptive participation. This nuanced behavior would likely be missed in traditional linear regression models, which assume a uniform relationship across all ranges of the predictor variables (Friedman, 1991).

The MARS model reveals critical interactions between socio-economic and demographic variables that collectively influence family planning outcomes. Notably, it identifies a significant synergistic effect between low educational attainment (women below junior high school education, X5) and limited access to family planning information (X7), where the combination shows a sharper decline in contraceptive use than either factor alone. These findings corroborate existing evidence about education and information access as key determinants of contraceptive uptake (Cleland et al., 2012; Sedgh et al., 2016).

The model's analytical power stems from its basis functions and adaptive knot placement, which detect threshold effects in the data. Three distinct patterns emerge: (1) participation plummets when participants exceed 30 years with sub-junior high education (BF10), (2) stagnates when poverty exceeds 60% (BF15), and (3) improves exponentially when education surpasses junior high level (BF5). These thresholds reflect real-world behavioral dynamics - for instance, workforce participation (X4) only significantly impacts contraceptive use after reaching certain employment levels, likely through increased autonomy and decision-making power (Samari, 2018).

These insights enable precisely targeted interventions: (1) Education-access deficient areas, mobile clinics staffed by local health workers paired with community education. (2) High-poverty regions (>60%): Integrated family planning-poverty reduction programs with conditional cash transfers. (3) Working women concentrations: Adjusted clinic hours to accommodate work schedules.

Approximately 17% of districts exhibit multiple risk factors requiring comprehensive interventions. The model's geographical clustering (visible in supporting figures) allows for efficient resource allocation, while basis function patterns serve as real-time performance indicators. This threshold-sensitive approach represents a paradigm shift from uniform programs to adaptive strategies that respond to local socioeconomic contexts, critical inflection points in predictor variables, emerging regional patterns through continuous monitoring.

By identifying high-priority subgroups (older, less-educated women in information-poor areas) and their specific barriers, the model enables Indonesia to implement demographically and geographically customized programs that maximize resource efficiency and program effectiveness.

.In summary, the MARS model not only provides accurate predictions but also valuable insights into the conditional relationships between predictors. It supports policy formulation by identifying specific population segments such as low-educated or older women with poor information access who may benefit the most from targeted interventions. This approach supports geographically and demographically customized strategies to improve family planning participation in Indonesia.

CONCLUSION

While the MARS model provides robust quantitative insights into family planning participation, several limitations should be acknowledged. First, the analysis relies on secondary data, which may not capture nuanced sociocultural factors (religious norms or gender dynamics) that influence contraceptive decisions. Second, the model's high R^2, while impressive, may reflect over-fitting to the sampled regions, necessitating validation in other provinces with distinct demographic profiles. Third, the current framework does not incorporate qualitative dimensions—such as community attitudes or healthcare provider biases, that could further explain observed thresholds.

Future research should address these gaps through: (1) Mixed-Methods Approaches: Combining MARS modeling with qualitative interviews to contextualize statistical thresholds (e.g., why education < junior high emerges as a critical barrier). (2) Geographical Expansion: Testing the model's generalizability in eastern Indonesian provinces, where healthcare access and cultural contexts differ substantially from Java-based data. (3) Dynamic Monitoring: Integrating real-time data (e.g., mobile health surveys) to track how basis function thresholds shift with policy interventions or socioeconomic changes. (4) Intersectional Analysis: Exploring interactions beyond socioeconomic variables, such as ethnicity or migration status, to identify hidden disparities.

Such advancements would enhance the model's utility for Indonesia's diverse settings while maintaining its core strength: transforming complex behavioral patterns into actionable policy levers.

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