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MODELLING MATHEMATICS LEARNING OUTCOMES USING A MULTIPREDICTOR SEMIPARAMETRIC REGRESSION APPROACH BASED ON SPLINE ESTIMATOR

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Abstract: Education is one of the points of Indonesia's SDGs which is stated in goal number 4. Mathematics is one of the subjects that contributes to the realizing national education goals. In the independent curriculum, the success of the learning process at school can be seen from the criteria for achieving learning objectives. In this article, we analyzed students' mathematics learning outcomes using a multi predictor semiparametric regression approach and interpreted the results with Spline estimator. The results shows that the differences between the types of classes greatly influence outcomes in learning mathematics, where social classes experienced a decrease of 2.435 percent compared to science classes. To increase outcomes in learning mathematics, the percentage of learning motivation must be more than 88 percent. Apart from that, high or low IQ cannot determine whether students' mathematics learning outcomes. Furthermore, by combining linear and nonlinear components in the model effectively, the overall accuracy based on the MAPE value is 7.87 percent, so that the model can be predict the actual value high accurately. Thus, the multi predictor semiparametric regression approach based on spline estimator can explain the mathematics learning outcomes model very well.
***Keywords**:* Learning outcomes; mathematics; multi predictor; spline estimator; statistics modelling

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Introduction

Education is one of the points of Indonesia's Sustainable Development Goals (SDGs) which is stated in goal number 4, quality education, namely ensuring inclusive and equitable quality education and increasing lifelong learning opportunities for all (Bappenas RI, 2024). One of the points of concern for the SDGs in this sector is quality education, one of which is the curriculum implemented by schools in the teaching and learning process. Freedom to learn is a program for freedom of thought and expression as a step to transform education for the realization of superior human resources. However, in the independent learning curriculum there is one thing that is a learning challenge, namely learning mathematics (Anggreini & Priyojadmiko, 2022). Mathematics is one of the subjects that contributes to the realization of national education goals and building a productive, creative, innovative, and insightful Indonesian nation. Since 2010, students' learning outcomes has been relatively low compared to other subjects because students have assumed that mathematics is a subject that is difficult to understand, so it is not liked by most students (Daimah & Suparni, 2023).

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Based on the researcher's first observations on students, the determination of majors was carried out by conducting psychological tests to determine students' IQ, interests and talents, and majors at school, as a determination for students to enter the science or social sciences major (Widodo, 2020). The major is carried out with the aim of making students focus on a particular group of sciences (Anestiviya et al., 2021). The science major will focus on learning about the sciences that study how nature works such as Physics, Chemistry, and Biology, while the social sciences major studies social interactions such as History, Economics, Geography, and Sociology (Muttaqin et al., 2024). Based on the results of the researcher's observations at the school, students' mathematics learning outcomes were still relatively low. This can be seen from the results of the teacher's meeting, where mathematics was the second ranked as a subject with a low average, followed by English. Based on this, mathematics is one of the problems in low learning outcomes (Nabillah & Abadi, 2019).

In the independent curriculum, the success of the learning process in school can be seen from the criteria for achieving learning objectives. Learning goal achievement criteria is a series of criteria or indicators that show the extent to which students have achieved competency in learning goals. However, the most important factor in learning achievement can be assessed from the level of intelligence (Andari & Lestari, 2023). There are two general factors that influence students' learning achievement, namely internal factors (from within themselves) dominated by students' psychological conditions which include intellectual intelligence (IQ), motivation and learning interest, and external factors which include the environment in the family, school, and society. Thus, the factors with a greater contribution to learning achievement are internal factors, one of them is IQ, which is a parameter of human intelligence (Lestari et al., 2021).

Intellectual intelligence is the cognitive intelligence possessed by individuals as a potential provision to act purposefully and think meaningfully so that they can solve a problem (Poveda et al., 2021). The public assumes that someone with a high IQ can achieve high achievements. However, most students who have a high IQ but do not be motivated will result in someone being lazy in studying, so that learning motivation is a series of internal and external encouragement for students to make changes in behavior (Dong & Liu, 2022). Apart from that, learning interest are also a factor that influences the achievement of teaching and learning objectives (Zaifullah et al., 2021). Learning interests are a student’s sense of interest where the student wants to explore something, so that changes occur in the student which will foster a sense of liking and can raise self-enthusiasm in teaching and learning (Ruf et al., 2022). However, to analyze students' interest in learning mathematics, modeling is necessary to see functional relationships, namely statistical modeling using regression analysis.

Based on the factors that influence student’s mathematics learning outcomes, efforts are needed to achieve learning, namely statistical modeling. Statistical modeling is one way to analyze factors that influence the achievement of learning objectives. In general, statistical modeling is a theory that is generally used in science and technology for research on the relationships between real phenomena in everyday life. One of the statistical modeling used is regression analysis. Regression analysis is a statistical analysis used to predict, estimate curves, and interpret the relationship between predictor variables and response variables (Khasanah, 2021). Approaches to the pattern of relationships between predictor variables and response variables include parametric and nonparametric regression approaches (Fernandes, 2022). Parametric regression is used when modeling the relationship between predictor variables and response variables is known or has a certain function, including linear, quadratic, cubic, exponential, and so on. In using parametric regression, assumptions must be met by the data being analyzed (Pardoe, 2020). However, the problem that occurs is that not all data can be approached with parametric regression because not all cases have information on the form of a relationship or regression curve between predictor variables and response variables. Therefore, for data that does not require a pattern of relationships between variables, a non-parametric approach can be used (Chamidah & Lestari, 2022).

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Nonparametric regression is used if the form of the relationship between the response variable and the predictor variable is unknown. The curve in nonparametric regression is assumed to be smooth or contained within a certain function. Nonparametric regression is considered more flexible because it does not require assumptions like parametric regression. In addition, the shape of the curve is determined by the data itself without the influence of subjectivity originating from the researcher (Chamidah & Lestari, 2022). However, there are times when the data used in research has a pattern of relationships between predictor variables and response variables, some of which have certain relationships and some of the patterns are unknown. Therefore, if the model has parametric components and non-parametric components, a semiparametric regression approach can be used (Khairunnisa et al., 2020).

The semiparametric regression estimator used by researchers is the least square spline estimator. The least square spline estimator is a polynomial function that is truncated at the p^{th} order, where in this function there are connecting points called knot points (Melati et al., 2024). Knot points can be said to be fusion points that indicate patterns of changes in data behavior. Meanwhile, the order value shows the height of the polynomial degree in the function. These knot points and orders are then used to determine the spline regression model. Splines can resolve data patterns that show sharp increases or decreases with the help of knot points (Eubank & Randall, 1999).

Further research related to learning outcomes using semiparametric regression is Gusti (2011) which modeling the national exam results on influencing factors, namely *try out* scores and IQ scores. The results show that IQ has a more direct influence on students' intelligence levels and there are other variables that have a direct influence but were not used in the research. Research from Ramadhan (2019) modeling the scores of the computer-based national exam (UNBK) in West Nusa Tenggara (NTB). The results of the research show that there is one variable that has a significant influence, namely the learning outcomes report card variable. Similar research was conducted by Hidayati et al. (2020) who discussed further the estimation of confidence intervals for UNBK values based on a multi-response semiparametric regression model with a truncated spline estimator. The results showed that increasing report card scores, gender, and school accreditation predicate scores influence increasing UNBK scores in each subject school. Meanwhile, distance, parental education, and SE values fluctuate at certain nodes for UNBK values in each lesson.

Based on some of the explanations above, no one has modeled students' mathematics learning outcomes using semiparametric regression, so researchers are interested in conducting research on students' mathematics learning outcomes in the independent curriculum which will be novelty in this research. The analysis of the mathematics learning interest model is carried out using two approach methods, namely parametric dummy as a parametric predictor variable, namely type class (natural science and social science) and non-parametric spline as non-parametric predictors which include percentage of learning motivation, learning interest, and IQ which will then be estimated using a truncated spline estimator. This research will also analyze in more detail the factors that influence students' mathematics learning outcomes with the hope of being able to provide recommendations and solutions to the problem of achieving learning objectives.

Methods

Data Collection

The data used in this research is primary data obtained from Senior High School in Al-Islam Krian, Sidoarjo Regency. The variables used in this research include class $(\boldsymbol{x_1})$ as a dummy variable in parametric component predictor, percentage of learning motivation $(\boldsymbol{x_2})$, learning interest $(\boldsymbol{x_3})$, intelligence quotient $(\boldsymbol{x_4})$ as a nonparametric component predictor, and students' mathematics learning outcomes as a response variable $(\boldsymbol{y})$.

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Reseacrh Steps

The steps used in this research are as follows:

1. Describe students' mathematics learning outcomes and the factors that influence it based on the average value and variance, and create a scatter plot between the response variable and the predictor variable.
2. Modeling students' mathematics learning outcomes using the multi predictor semiparametric regression approach based on Least Square Spline estimator with the following stages:
   a. Input paired data (y_i, x_{ij}, t_{si}), where $i = 1,2, \dots, n$ representing the index of the number of observations; $j = 1$ represents the index of the number of parametric component variables; $s = 1,2,3$ represents the index of the number of nonparametric component variables.
   b. Test the correlation between the response variable and the predictor variable using the Pearson correlation test.
   c. Estimating a multi predictor semiparametric regression model based on the Spline estimator with stages according to the algorithm and program.
   d. Make plots of observation data and estimation results of response variables against predictor variables.
   e. Calculate MAPE and R^2 values.
3. Interpreting the results of modeling students' mathematics learning outcomes using a multi predictor semiparametric regression approach based on a least square spline estimator.

Result and Disccussion

Descriptive Statistics

This study examines the factors that influences student outcomes in learning mathematics, using a semiparametric regression model with a spline estimator to analyze several predictors. The following Table 1 are the characteristics of students' mathematics learning outcomes and several factors.

Table 1. Descriptive Statistics

Variable	Min	Max	Mean	Variance
Student outcomes in learning mathematics (y)	52	98	77.61	185.61
Percentage of Motivation Study (t_1)	0.40	0.98	0.79	0.018
Learning Interest (t_2)	0.42	0.99	0.81	0.017
Intelligence Quotient (IQ) (t_3)	70	118	96.46	118.03

Based on Table 1, information is obtained that the average outcomes in learning to understand math lessons is 77.61 with a variation of 185.61. Then, the average motivation to learn mathematics in students is 0.79 with a variation of 0.018. From these percentages, students' motivation to learn mathematics is quite high, but there is a high variation due to the influence of the specialization of science and social classes to understand mathematics. Furthermore, in terms of the suitability value of student learning interests for understanding math subjects is 0.81, and with a variation of 0.017. The importance of IQ in this study is to see the basic knowledge possessed by students who can capture information from explanations or information related to math subjects at school. The average IQ score of students on the object under study is 96.46 and the variation is 118.03.

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Determining Parametric and Nonparametric Component

Semiparametric models combine both parametric and nonparametric elements to understand complex relationships within data. To find out which components must be parametric and nonparametric, a scatter plot can be used between the response variable and the predictor variable as in Figure 1 as follows:

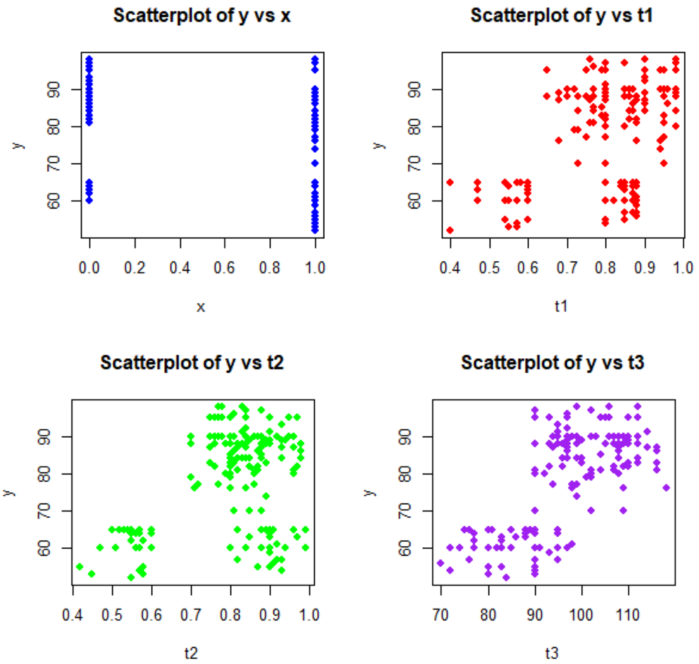

Figure 1. Scatter Plot the Response and Predictor Variables

Based on Figure 1, there are four scatter plots between the response variable and each predictor variables. Based on the plot results, the variable x tends to follow a certain pattern, namely following the linear form used, so that the variable x is called a dummy variable. In addition, the t_1, t_2, and t_3 plots are less likely to form a particular pattern and the relationship pattern tends to change the behavior of the sub-intervals. So, the conclusion of variables including parametric and nonparametric components as shown in Table 2.

Table 2. Summary of Parametric and Nonparametric Components

Variable	Notation	Description
Type of Class (Dummy)	(x)	Parametric Component
Percentage of Motivation Study	(t_1)	
Learning Interest	(t_2)	Nonparametric Component
Intelligence Quotient (IQ)	(t_3)	

Nonlinearity Test

Nonlinearity test using correlation and Ramsey test (RESET test) is a method used to determine the closeness of the relationship between two or more different variables described by the size of the correlation coefficient. In a correlation test, the strength of the relationship between two variables will be measured using the correlation coefficient. The correlation coefficient measures the degree of tendency between two variables to move together. The following are the results of correlation testing with Pearson correlation in Table 3.

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Table 3. Pearson Correlation and Ramsey Test

Variable	Correlation Coefficient	Ramsey Test	P-value	Decision
$(t_1) \rightarrow (Y)$	0.4743	2.1431	0.000	The model may have misspecifications, including non-linearity.
$(t_2) \rightarrow (Y)$	0.3666			
$(t_3) \rightarrow (Y)$	0.6961			

Based on Table 3, there is a correlation or linear relationship effect with the y variable, so it can be a criterion for determining the order used, namely using a linear order $(\rho = 1)$ and based on Ramsey Test, show that the model may have misspecifications, including non-linearity.

Modelling with Semiparametric Spline Truncated

Modelling outcomes in learning mathematics using a multi predictor semiparametric regression approach based on spline estimator depend on knot that used. The selection of optimal knot points is necessary to estimate the spline function. The number of knots (K) is the number of knots or the number of points. Changes in function behavior at different intervals. The knot points are in the quantile sample of unique (single) values as shown in Table 4.

Table 4. The Location of Knot Points Using Quantile

Variable	Knot Points
(t_1)	0.7625
	0.84
	0.88
(t_2)	0.79
	0.84
	0.90
(t_3)	90
	97
	107

One method that can be used to determine the optimal number and location of knots is the full-search method. The algorithm of the full-search method is based on the Generalized Cross Validation (GCV) method. The following are the results of determining the optimal knots selected based on the minimum GCV and MSE value as shown in Table 5.

Table 5. GCV Value with Combination Knots Point

Knot Points			GCV	MSE
t_1	0.7625	0.88	102.4507	95.5537
t_2	0.78	0.9	107.8743	100.6122
t_3	90	96	83.003	77.415

Based on Table 5, we can see that there is a minimum GCV at combination knots points, so that the best semiparametric regression approach based on spline truncated is model with two knots point on percentage of motivation study variable, two knots point on learning interest variable, and two knots

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point on Intelligence Quotient. After selecting the optimal knot points, the estimation process is carried out using the Ordinary Least Square (OLS) estimator, so that the estimated parameter values in the model are obtained as in Table 6 as follows:

Table 6. The Result of Estimation Parameters

Variable	Parameter	Estimation
Constant Semiparametric	$\hat{\gamma}_0$	-18.738
x	$\hat{\beta}_1$	-2.435
t_1	$\hat{\alpha}_{11}$	42.107
t_2	$\hat{\alpha}_{21}$	54.617
t_3	$\hat{\alpha}_{31}$	0.515
$(t_1 - \xi_{11})_+$	$\hat{\alpha}_{12}$	-91.290
$(t_1 - \xi_{12})_+$	$\hat{\alpha}_{13}$	145.640
$(t_2 - \xi_{21})_+$	$\hat{\alpha}_{22}$	-121.771
$(t_2 - \xi_{22})_+$	$\hat{\alpha}_{23}$	82.187
$(t_3 - \xi_{31})_+$	$\hat{\alpha}_{32}$	0.929
$(t_3 - \xi_{32})_+$	$\hat{\alpha}_{33}$	-1.396

Based on Table 6, the best spline truncated semiparametric regression model formed as follows:

$$\begin{aligned}\hat{y} = {} & -18.738 - 2.435x + 42.107t_1 - 91.29(t_1 - 0.7625)_+ + 145.64(t_1 - 0.88)_+ + \\ & 54.617\, t_2 - 121.77(t_2 - 0.785)_+ + \ 82.187(t_2 - 0.90)_+ + 0.515\, t_3 + \\ & 0{,}929(t_3 - 90)_+ - 1.396(t_3 - 96)_+\end{aligned} \tag{1}$$

Based on (1), the variables that significantly influence is as follows:

1. The type of class as dummy variables $(0, 1)$ with other assumptions of constant variables is as follows:
$$\hat{y} = -18.738 - 2.435x \tag{2}$$
Based on (2), if type of class is sciences ($x = 0$), then there is no decrease related to the variable student outcomes in learning mathematics. If type of class is social ($x = 1$), then there is a decrease related to the variable student outcomes in learning mathematics by 2.435.
2. Percentage of Motivation Study with assumption other variables are constant is as follows:
$$\hat{y} = \begin{cases} 42.017t_1, & t_1 < 0.7625 \\ 69.608 - 49.18t_1, & 0.7625 \leq t_1 \leq 0.88 \\ -58.55 + 96.457t_1, & t_1 \geq 0.88 \end{cases} \tag{3}$$
Based on (3), for student with a learning motivation percentage between 76.25 percent and 88 percent, every 1 percent increase in learning motivation will decrease their outcomes in learning mathematics by 49.18. For student with a learning motivation percentage above 88 percent, every 1 percent increase in learning motivation will increase their outcomes in learning mathematics by 96.45.
3. Learning interest who have been immunized with assumption other variables are constant is as follows:
$$\hat{y} = \begin{cases} 54.617t_2, & t_2 < 0.785 \\ 95.59 - 67.15t_2, & 0.785 \leq t_2 \leq 0.90 \\ 15.03 + 21.62t_2, & t_2 \geq 0.90 \end{cases} \tag{4}$$
Based on (4), for student with a learning interest percentage between 78.5 percent and 90 percent, every 1 percent increase in learning interest will decrease their outcomes in learning

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mathematics by 67.15. For student with a learning interest above 90 percent, every 1 percent increase in learning interest will increase their outcomes in learning mathematics by 21.62.

4. Intelligence Quotient with assumption other variables are constant is as follows:

$$\hat{y} = \begin{cases} 0.515t_3, & t_3 < 90 \\ -83.61 + 1{,}444\, t_3, & 90 \leq t_3 < 96 \\ 50.40 + 0{,}048\, t_3, & t_3 \geq 96 \end{cases} \quad (5)$$

Based on (16), For student with IQ between 90 and 97, every 1 increase in IQ will increase their outcomes in learning mathematics by 1.44 percent. For student with IQ above 97, every 1 increase in IQ will increase their outcomes in learning mathematics by 4.8 percent.

Accuracy Model

Mean Absolute Percentage Error (MAPE) and R-square is a common metric for evaluating the accuracy of a predictive model. It is particularly useful in semiparametric regression models because it expresses prediction accuracy as a percentage, making it easy to interpret and compare across different datasets and models. The following is the MAPE and R-square value of the model that has been formed as shown in Table 7.

Table 7. The Accuracy Model Using MAPE

Model	MAPE	R^2	Result
Training	7.67%	67.12%	High Accurate
Testing	8.07%	75.20%	High Accurate
Overall	7.87%	71.16%	High Accurate

Based on Table 7, it shows that the overall model accuracy has a MAPE value of 7.87% where the value is less than 10%, so the model can predict the actual value high accurate. In addition, from the r-square results, a value of 71.16% was obtained. This can be explained by the the predictor variables for the response variable by 71.16%, and 29.84% is explained by variables outside this study. So that, the application of multi predictor semiparametric regression with a spline estimator can explained by the whole model.

Conclusion

The multipredictor semiparametric regression model based on spline estimators is used to determine students' mathematics learning outcomes. The results how that the different types of science and social classes greatly influence interest in learning mathematics. This can be seen from the social classes which experienced a decrease in outcomes of 2.435 percent compared to science classes. To increase outcomes in learning mathematics, we must have a higher percentage of learning motivation, namely more than 88 percent. Apart from that, based on the interpretation, it is known that high or low IQ does not determine whether a person's outcomes in learning mathematics. Furthermore, by combining linear and nonlinear components in the model effectively, we can see that the overall accuracy of the model has a MAPE value of 7.87%, where the value is less than 10%, which means the model is able to predict the actual value high accurately with R^2 the value obtained is 71.16%. Therefore, the application of multi predictor semiparametric regression based on spline estimator can explain the model very well and this approach provides deeper insights into the various factors that influence educational interactions, thereby paving the way for more appropriate and effective educational policies and practices.

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