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ANALYSIS OF PATH NONPARAMETRIC TRUNCATED SPLINE MAXIMUM CUBIC ORDER IN BANKING CREDIT OF RISK BEHAVIOR MODEL

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ABSTRACT

Path analysis tests the relationship between variables through cause and effect. The assumption of linearity must be met before conducting further tests on path analysis. If the shape of the relationship is nonlinear and the shape of the curve is unknown, a nonparametric approach is used, one of which is a truncated spline. The purpose of this study is to estimate the function and obtain the best model on the nonparametric truncated spline path of linear, quadratic, and cubic orders with 1 and 2-knot points and determine the significance of the best function estimator in banking credit of risk behavior model through the jackknife resampling method. This study uses secondary data through questionnaires to KPR debtor consumers, as many as 100 respondents. Based on the results of the analysis, it is known that the best-truncated spline nonparametric path model is the quadratic order of 2 knots with a coefficient of determination of 85.50%; the significance of the best-truncated spline nonparametric path estimator shows that all exogenous variables have a significant effect on endogenous variables.

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1. INTRODUCTION

Statistics is a science or art related to methods of data collection, data analysis, and interpretation of analysis results to produce helpful information in making decisions and drawing conclusions [1]. Statistics are divided into two categories: descriptive and inferential. Descriptive statistics provides various techniques for presenting collections of observations or data, such as tables, graphs, and averages. After getting a summary of the data, a conclusion can be formed by applying inferential statistics [2]. Many analyses can be used in data processing, including regression analysis. According to [3], regression analysis is a statistical analysis used to model the relationship between predictor and response variables. Although regression analysis can determine the relationship between several predictor variables and response variables, this path analysis still has limitations in dealing with models with more complex relationships. Path analysis was developed to overcome the weaknesses of regression analysis.

Path analysis is a statistical method used to test the relationships between variables in the form of cause and effect. The equation in path analysis involves at least one exogenous variable, at least one mediating variable, and one or more endogenous variables [4]. According to [5], six assumptions must be met in path analysis: (1) the relationship between variables is linear and additive, (2) the residuals are normally distributed, (3) the pattern of the relationship between variables is recursive, (4) the minimum endogenous variable is on an interval measurement scale, (5) the research variables are measured without error, and (6) the model being analyzed is specified based on relevant theories and concepts. The linearity assumption is the first assumption that must be met before path analysis is carried out. If the linearity assumption is met, parametric path analysis is the suitable model. However, if the linearity assumption is not met, there are two possibilities: nonlinear path analysis or nonparametric path analysis [6].

Nonparametric path analysis is a nonparametric model that is not bound by the assumption that the shape of the curve is known. In this model, the data can determine the most appropriate curve shape. The regression curve is assumed to be contained in an infinite dimensional function space and is a smooth function [7]. A nonparametric approach that is often used is the spline approach. One of the spline functions that is often used is the truncated spline. Truncated spline is part or pieces of polynomials that have continuous and segmented (truncated) properties. The advantage of a truncated spline is that it tends to find its form of function estimator when there is a shift in the data pattern and can show sharp up and down points, which helps correct patterns in the data because the spline has a joint point that shows the occurrence of data behavior patterns called knot points [6]. Previous studies that applied nonparametric truncated spline path analysis were [8], which modeled the timeliness of bank credit. Similar research was conducted by [9], who modeled the case of community welfare with the role of government as a mediating variable.

The use of statistical methods, especially in government, has a vital role in determining policies and steps taken by the government in overcoming problems in society. Housing needs are one of the primary needs of a person besides the need for food and the need for clothing. Over time, population growth in Indonesia has increased, urging the government to participate in overcoming this problem, namely with KPR (Home Ownership Credit). KPR is a program given to individual customers who will buy or repair houses by banks. The purpose of the government making a policy in the form of KPR is to increase the ability of the community to buy a home. The main target of providing mortgages is for groups of people who have middle to lower income.

The importance of customers paying credit for the bank will improve the bank's reputation. Banks can adequately carry out their functions in national development, increase profits or profits from banks, and also have the opportunity to market other products such as service products and fund products. In addition, bank credit is used to encourage general economic growth in specific sectors. Many factors affect credit payments: character, willingness to pay, and fear of paying late. According to [10], character is a person's personality. The personality of the people who will be given financing must be genuinely trustworthy. A person's character will affect their willingness to pay. Willingness to pay is the willingness of the credit applicant to pay the payment burden according to the predetermined credit amount [11]. Every customer must have specific fears and concerns in their life. One of them is the fear of paying late. This fear is a natural thing, where each customer can determine the selection of the weight of the mortgage payment burden. [12]. This fear encourages a person not to have problems with credit. If there are problems in credit, economic growth will be hampered. Paying credit by the time that has been determined is very important. Based on the description above, the purpose of this study is to estimate the function and get the best model on nonparametric truncated spline lines of linear, quadratic, and cubic orders with 1 and 2-knot points and determine the significance of the best function estimator in the banking credit risk model through the jackknife resampling method.

2. RESEARCH METHODS

2.1 Data

The data used in this study are secondary data from a research grant [13]. he population of this study is Bank X KPR debtor customers in Jakarta Province, Indonesia. A total of 100 participated in this study. The sampling technique used was judgment sampling. The study used latent variables on a Likert scale. The variables measured were Character (X), Willingness to Pay (Y_1), Fear of Paying Late (Y_2), and Respondent Paying Behavior (Y_3). All variables have gone through validity and reliability checks by researchers with the results that all questionnaire items were valid and reliable so that they could be used for further analysis.

2.2 Research Model and Research Steps

The research model used can be seen in Figure 1.

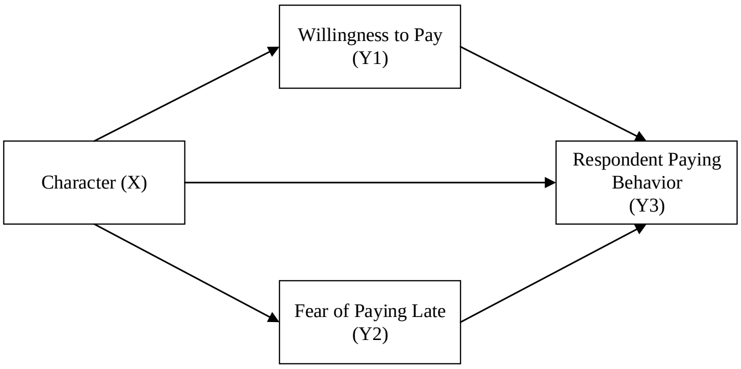

Figure 1. Research model

The model used in Figure 1 will use nonparametric path analysis truncated spline. This study uses the help of R Studio Software. The steps in this study are as follows:

1. Prepare secondary data.
2. Scaling variable data using the Summated Rating Scale method.
3. Testing the linearity assumption using the Regression Specification Error Test (RESET) method. If the linearity assumption is not met and the nonlinear form is unknown, then continue with nonparametric path analysis.
4. Estimating the path function with truncated spline linear, quadratic, and cubic orders with 1 and 2-knot points using the Ordinary Least Square method.
5. Obtaining the results of the function estimate of each polynomial degree, namely linear, quadratic, and cubic, with 1 and 2 knot points.
6. Selecting the best model and optimal knot points based on the GCV (Generalized Cross Validation) coefficient.
7. Calculating the coefficient of determination (R2) for each nonparametric path model.
8. Selecting the best model of nonparametric path analysis truncated spline based on the most significant (R2) value.
9. Conducting hypothesis testing of the path function of the best model with t-test statistics using replication values and standard errors generated from the jackknife resampling process.
10. Interpret the results of estimating the nonparametric path function of the best-truncated spline model and conclude from the analysis results.

2.3 Truncated Spline Nonparametric Path Analysis

The parametric path model can still not be applied when the shape of the regression curve is unknown, and the linearity assumption is not met. Therefore, a nonparametric path model can be applied, which is a development of nonparametric regression. Estimating the path function can be used with a nonparametric regression approach that shows the relationship between one endogenous variable and one or more exogenous variables (multi-exogenous) involving n observations [14]. General equation model of simple truncated spline nonparametric path analysis shown in Equation (1) [15].

$$Y_{1i} = f\left(x_{1i}\right) + \varepsilon_{1i} \tag{1}$$

The general form of the truncated spline function with degree-p polynomials is presented in Equation (2).

$$\hat{f}(X_{1i}) = \hat{\beta}_0 + \sum_{j=1}^{p} \hat{\beta}_j X_{1i}^j + \sum_{k=1}^{K} \delta_k \left(X_{1i} - K_k\right)_+^p \tag{2}$$

Function $\left(X_i - K_k\right)_+^p$ is a truncated function given by:

$$(X_i - K_k)_+^p = \begin{cases} (X_i - K_k)^p & ; X_i \geq K_k \\ 0 & ; X_i < K_k \end{cases}$$

Explanation:
$i = 1, 2, 3, \ldots, n$; n: many observations
$j = 1, 2, 3, \ldots, p$; $p \geq 1$; p: spline order
$k = 1, 2, 3, \ldots, k$; k: number of knot points

2.4 Optimal Knot Point Selection

The spline nonparametric path model is an analytical model that uses a nonparametric approach, where the least-squares estimation with optimal knot points is selected based on the value of the smallest GCV (Generalized Cross Validation) [6]. The best spline estimator is obtained from the optimal knot point. The best spline function is obtained if the optimal knot point is obtained. The GCV formula is shown in Equation (3):

$$GCV(\mathbf{K}) = \frac{MSE(\mathbf{K})}{\left[n^{-1} trace(\mathbf{I} - \mathbf{A}(\mathbf{K}))\right]^2} \tag{3}$$

with $MSE(\mathbf{K}) = n^{-1} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$, $\mathbf{K}$ is the knot point and matrix $\mathbf{A}(\mathbf{K})$ obtained from:

$$A[\mathbf{K}] = \mathbf{X}[\mathbf{K}]\left(\mathbf{X}[\mathbf{K}]^{\mathrm{T}} \mathbf{X}[\mathbf{K}]\right)^{-1} \mathbf{X}[\mathbf{K}]^{\mathrm{T}} \tag{4}$$

Equation (2.46) is a function of the knot points and $\mathbf{K} = \left(K_1, K_2, \ldots, K_k\right)^{\mathrm{T}}$ are the knot points.

2.5 Model Validity

The coefficient of determination is an indicator of model validity. The coefficient of determination measures the contribution of predictor variables to the response variable. The coefficient of determination was used to determine how much the model could explain diversity. The higher the coefficient of determination, the better the model. According to [16], the coefficient of determination formula can be seen in the following Equation (5):

$$R^2 = 1 - \frac{\sum_{k=1}^{3} \sum_{i=1}^{n} (y_{ki} - \hat{f}_{ki})^2}{\sum_{k=1}^{3} \sum_{i=1}^{n} (y_{ki} - \bar{y}_k)^2} ; 0 \leq R^2 \leq 1 \tag{5}$$

Explanation:

y_{ki} : the i-th value of the endogenous variable

$\hat{f}_{ki}$: i-th function estimator for endogenous variables

$\bar{y}_k$: average of endogenous variables

2.6 Resampling Method

Resampling is the process of re-sampling from existing samples to obtain new samples. The new samples are obtained from the original samples taken randomly, either with or without replacement. The application of the resampling method allows the validity of data free from assumptions or, in other words, does not require the assumption of normality. The jackknife method is a resampling method without returns, therefore there is an intertwined relationship in each resampling process. Suppose there is an initial sample $x = (x_1, x_2, \ldots, x_n)$ and $\hat{\theta} = s(x)$ is the estimate of a parameter. The steps for estimating the standard error of the jackknife are as follows [17].

1. Resampling by deleting 1 row of data in each jackknife sample.

$$x_{(i)} = x_1, x_2, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n$$

2. Calculating the corresponding jackknife replications for each jackknife sample.

$$\hat{\theta}_{(i)} = s(x_{(i)}); i = 1, 2, \ldots, n \tag{6}$$

3. Estimating the standard error using the standard deviation for the jackknife replicated n times.

$$\widehat{SE}_{jack} = \left[\frac{n-1}{n} \sum_{i=1}^{n} \left(\hat{\theta}_{(i)} - \hat{\theta}_{(.)} \right)^2 \right]^{1/2} \tag{7}$$

2.7 Hypothesis Testing

Hypothesis testing using test statistics, where parameter estimates and standard errors from jackknife resampling results. Hypothesis testing with test statistics is done using the following formula:

$$t \text{ test statistics} = \frac{\hat{\beta}_j}{SE_{\hat{\beta}_j}} \sim t_{n-1} \tag{8}$$

The hypothesis used for the test statistics in **Equation (8)** is as follows.

$$H_0 : \beta_j = 0$$

$$H_1 : \beta_j \neq 0$$

Furthermore, the results of the t test statistics are compared with the t table. The test criteria, namely if the test statistic $t > t_{\frac{\alpha}{2}(n-1)}$ then H_0 is rejected, which means that there is a significant influence between exogenous variables on endogenous variables.

2.8 Research Variables

The research uses latent variables from the Likert measurement scale. The variables measured are Character ($\boldsymbol{X}$), Willingness to Pay ($\boldsymbol{Y_1}$), Fear of Paying Late ($\boldsymbol{Y_2}$), and Obedient Paying Behavior ($\boldsymbol{Y_3}$). The variables used will be described in several indicators, as in **Table 1**.

Table 1. Research Variables

Variable	Indicators
Character (X_1)	Faith and responsibility ($X_{1.1}$) Nature or Disposition/Lifestyle ($X_{1.2}$) Payment Commitment ($X_{1.3}$)

Variable	Indicators
	Payment Consultation ($Y_{1.1}$)
	Payment Documentation ($Y_{1.2}$)
Willingness to Pay (Y_1)	Payment Method ($Y_{1.3}$)
	Payment deadline ($Y_{1.4}$)
	Payment fund allocation ($Y_{1.5}$)
	Physical Symptoms ($Y_{2.1}$)
Fear of Paying Late (Y_2)	Behavioral Symptoms ($Y_{2.2}$)
	Cognitive Symptoms ($Y_{2.3}$)
	Timeliness ($Y_{3.1}$)
Obedient Paying Behavior (Y_3)	Data Accuracy ($Y_{3.2}$)
	Sanctions ($Y_{3.3}$)

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics

Descriptive statistics were conducted on two data, namely the average score before scaling and the average score after scaling. The results of descriptive statistics can be seen in **Table 2**.

Table 2. Descriptive Statistics

Variable	Average score before scaling	Average score after scaling
Character (X)	3.059 (60.18%)	2.901
Willingness to Pay (Y_1)	2.966 (49.32%)	2.953
Fear of Paying Late (Y_2)	3.029 (50.58%)	2.847
Obedient Paying Behavior (Y_3)	3.008 (50.16%)	2.820

Based on **Table 2**, descriptive statistics are known before and after scaling. Scaling in this study uses a summated rating scale and is used for path analysis. The average value of all variables is 2.5 to 3.5 or 40% to 60%, meaning that most mortgage debtor customers in Jakarta have a moderate level of character, willingness to pay, and fear of late payment. The average behavior of paying compliance is 3.008 or 50.16%, meaning that most mortgage debtor customers in Jakarta have a moderate level of compliance. While the average value after scaling cannot be interpreted, it is helpful for further analysis.

3.2 Linearity Test

The results of the linearity test with Ramsey's RESET are presented in **Table 3**.

Table 3. Ramsey's RESET Linearity Test Results

Variable	P-value	Relationship
Character (X) to Willingness to Pay (Y_1)	0.001	Non-linear
Character (X) to Fear of Paying Late (Y_2)	0.023	Non-linear
Character (X) to Obedient Paying Behavior (Y_3)	<0.001	Non-linear
Willingness to Pay (Y_1) to Obedient Paying Behavior (Y_3)	0.006	Non-linear
Fear of Paying Late (Y_2) to Obedient Paying Behavior (Y_3)	0.005	Non-linear

Based on **Table 3**, it can be seen that the p-value $< \alpha$ (0.05), then reject H_0. So, it can be concluded that the relationship between variables is not linear and the form of nonlinearity is not or not yet known. It was so using a nonparametric path analysis approach.

3.3 Selection of the Best-Truncated Spline Nonparametric Path Model

If the knot points are optimal, the best-truncated spline nonparametric path model is obtained. We must find the smallest GCV value to get the optimal knot point. The comparison between GCV and R2 of each model can be seen in **Table 4**.

Table 4. Comparison of GCV and R^2 of each Model

Order	Knot Points	GCV Model	R^2
Linear	1	0.5736	0.8294
	2	0.5627	0.8491
Quadratic	1	0.5625	0.8487
	2	0.5617	0.8504
Cubic	1	0.5673	0.8414
	2	0.5637	0.8477

Table 4 shows that the smallest GCV value of 0.5617 and the largest R2 value of 0.8504 were obtained in the nonparametric truncated spline path model of quadratic order 2 knots. The determination coefficient is 85.04%, meaning that the model formed explains 85.04% of the diversity, and other factors outside the banking credit risk model explain the remaining 14.96%..

3.4 Final Model (2 Knot Point Quadratic Truncated Spline Nonparametric Path Model)

The best-truncated spline nonparametric path model is in quadratic order with 2-knot points. Here are the optimal knot points and model goodness test on the best model.

Table 5. Optimal Knot Point and Model Goodness Test on Quadratic Model with 2-Knot Points

Variable	Optimal Knots	Model Goodness Test
Character (X) to Willingness to Pay (Y_1)	K_{11} = 2.62 K_{12} = 3.46	GCV = 0.5588 R^2 = 0.8550
Character (X) to Fear of Paying Late (Y_2)	K_{21} = 2.71 K_{22} = 3.57	
Character (X) to Obedient Paying Behavior (Y_3)	K_{31} = 2.54 K_{32} = 3.04	
Willingness to Pay (Y_1) to Obedient Paying Behavior (Y_3)	K_{41} = 2.26 K_{42} = 3.44	
Fear of Paying Late (Y_2) to Obedient Paying Behavior (Y_3)	K_{51} = 2.51 K_{52} = 2.74	

Based on Table 5, the GCV value is 0.5588, and the R2 value is 85.50%. It means that the model formed explains the diversity of endogenous variables by 85.5%, and the remaining 14.5% is explained by other factors that cannot be known in the model. The results of the path model estimation are as follows.

$$\hat{f}_{1i} = -8.12 + 7.27X_i - 1.18X_i^2 + 0.62(X_i - 2.62)_+^2 + 2.75(X_i - 3.46)_+^2$$

$$\hat{f}_{2i} = -12.41 + 11.26X_i - 2.08X_i^2 + 2.41(X_i - 2.71)_+^2 - 5.67(X_i - 3.57)_+^2$$

$$\begin{aligned}\hat{f}_{3i} &= 1.36 - 10.18X_i + 2.41X_i^2 - 4.69(X_i - 2.54)_+^2 + 2.19(X_i - 3.04)_+^2 + 11.79\hat{f}_{1i} - 2.71\hat{f}_{1i}^2 \\ &\quad + 2.89(\hat{f}_{1i} - 2.26)_+^2 - 2.73(\hat{f}_{1i} - 3.44)_+^2 - 1.47\hat{f}_{2i} + 0.41\hat{f}_{2i}^2 - 0.38(\hat{f}_{2i} - 2.51)_+^2 \\ &\quad - 0.29(\hat{f}_{2i} - 2.74)_+^2\end{aligned}$$

3.5 Hypothesis Testing on the Best Model

Jackknife resampling is performed by removing two random observations at each resampling stage. Resampling was performed 1000 times. The results of the best-truncated spline nonparametric path model estimator after jackknife resampling are the following.

$$\hat{f}_{1i} = -8.14 + 7.28X_i - 1.18X_i^2 + 0.62(X_i - 2.62)_+^2 + 2.74(X_i - 3.46)_+^2$$
$$\hat{f}_{2i} = -12.44 + 11.28X_i - 2.08X_i^2 + 2.42(X_i - 2.71)_+^2 - 5.66(X_i - 3.57)_+^2$$
$$\hat{f}_{3i} = 4.41 - 10.16X_i + 2.39X_i^2 - 4.54(X_i - 2.54)_+^2 + 1.98(X_i - 3.04)_+^2 + 14.41\hat{f}_{1i} - 3.33\hat{f}_{1i}^2$$
$$+3.58(\hat{f}_{1i} - 2.26)_+^2 - 3.11(\hat{f}_{1i} - 3.44)_+^2 - 6.74\hat{f}_{2i} + 1.60\hat{f}_{2i}^2 - 3.59(\hat{f}_{2i} - 2.51)_+^2 + 2.06(\hat{f}_{2i} - 2.74)_+^2$$

with a truncated function:

$$(X_i - 2.62)_+^2 = \begin{cases} (X_i - 2.62)^2 & ; X_i \geq 2.62 \\ 0 & ; X_i < 2.62 \end{cases}$$

$$(X_i - 3.46)_+^2 = \begin{cases} (X_i - 3.46)^2 & ; X_i \geq 3.46 \\ 0 & ; X_i < 3.46 \end{cases}$$

$$(X_i - 2.71)_+^2 = \begin{cases} (X_i - 2.71)^2 & ; X_i \geq 2.71 \\ 0 & ; X_i < 2.71 \end{cases}$$

$$(X_i - 3.57)_+^2 = \begin{cases} (X_i - 3.57)^2 & ; X_i \geq 3.57 \\ 0 & ; X_i < 3.57 \end{cases}$$

$$(X_i - 2.54)_+^2 = \begin{cases} (X_i - 2.54)^2 & ; X_i \geq 2.54 \\ 0 & ; X_i < 2.54 \end{cases}$$

$$(X_i - 3.04)_+^2 = \begin{cases} (X_i - 3.04)^2 & ; X_i \geq 3.04 \\ 0 & ; X_i < 3,.04 \end{cases}$$

$$\left(\hat{f}_{1i} - 2.26\right)_+^2 = \begin{cases} \left(\hat{f}_{1i} - 2.26\right)^2 & ; \hat{f}_{1i} \geq 2.26 \\ 0 & ; \hat{f}_{1i} < 2.26 \end{cases}$$

$$\left(\hat{f}_{1i} - 3.44\right)_+^2 = \begin{cases} \left(\hat{f}_{1i} - 3.44\right)^2 & ; \hat{f}_{1i} \geq 3.44 \\ 0 & ; \hat{f}_{1i} < 3.44 \end{cases}$$

$$\left(\hat{f}_{2i} - 2.51\right)_+^2 = \begin{cases} \left(\hat{f}_{2i} - 2.51\right)^2 & ; \hat{f}_{2i} \geq 2.51 \\ 0 & ; \hat{f}_{2i} < 2.51 \end{cases}$$

$$\left(\hat{f}_{2i} - 2.74\right)_+^2 = \begin{cases} \left(\hat{f}_{2i} - 2.74\right)^2 & ; \hat{f}_{2i} \geq 2.74 \\ 0 & ; \hat{f}_{2i} < 2.74 \end{cases}$$

The following is a hypothesis testing table using t-test statistics and the interpretation of direct effects between variables.

Table 6. Hypothesis Testing

Relationship	Estimation	Coefficient	P-value	Decision
$X_1 \to Y_1$	$\hat{\beta}_{11}X_1$	7.28	<0.001	Significant
	$\hat{\beta}_{21}X_1^2$	-1.18	0.113	Not Significant
	$\hat{\beta}_{31}(X_1 - K_{11})^2$	0.62	0.279	Not Significant
	$\hat{\beta}_{41}(X_1 - K_{12})^2$	2.74	0.001	Significant
$X_1 \to Y_2$	$\hat{\beta}_{12}X_1$	11.28	<0.001	Significant
	$\hat{\beta}_{22}X_1^2$	-2.08	0.009	

Relationship	Estimation	Coefficient	P-value	Decision
	$\hat{\beta}_{32}(X_1 - K_{21})^2$	2.42	0.003	
	$\hat{\beta}_{42}(X_1 - K_{22})^2$	-5.66	<0.001	
$X_1 \rightarrow Y_3$	$\hat{\beta}_{13}X_1$	-10.16	<0.001	Significant
	$\hat{\beta}_{23}X_1^2$	2.39	0.003	
	$\hat{\beta}_{33}(X_1 - K_{31})^2$	-4.54	<0.001	
	$\hat{\beta}_{43}(X_1 - K_{32})^2$	1.98	0.012	
$Y_1 \rightarrow Y_3$	$\hat{\beta}_{53}Y_1$	14.41	<0.001	Significant
	$\hat{\beta}_{63}Y_1^2$	-3.33	<0.001	
	$\hat{\beta}_{73}(Y_1 - K_{41})^2$	3.58	<0.001	
	$\hat{\beta}_{83}(Y_1 - K_{42})^2$	-3.11	<0.001	
$Y_2 \rightarrow Y_3$	$\hat{\beta}_{93}Y_2$	-6.74	<0.001	Significant
	$\hat{\beta}_{103}Y_2^2$	1.60	0.041	
	$\hat{\beta}_{113}(Y_2 - K_{51})^2$	-3.59	<0.001	
	$\hat{\beta}_{123}(Y_2 - K_{52})^2$	2.06	0.010	

3.6 Direct Effect of Character (X) to Willingness to Pay (Y_1)

The direct influence between the variable Character (X) to Willingness to Pay (Y_1) can be described as in **Figure 2**.

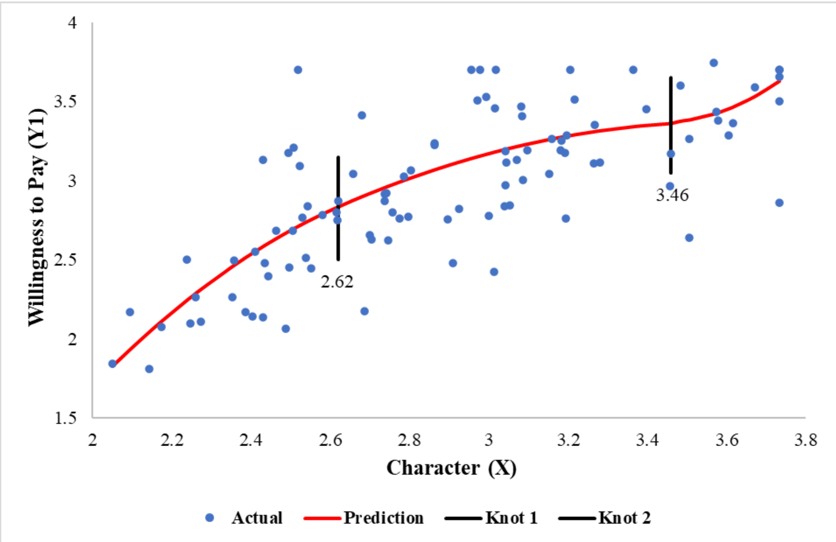

Figure 2. Direct effect X on Y_1

Testing the direct effect between Character (X) to Willingness to Pay (Y_1) on the quadratic order truncated spline nonparametric path model with 2-knot points is divided into three regimes. These three conditions show that the better a person's character, the higher the willingness to pay. A person with good characteristics, such as a high credit score, job stability, education level, and good track record, will directly increase a person's willingness to pay. Bank X can pay attention to the characteristics of a person that can increase the customer's willingness to pay according to the specified time. The results of hypothesis testing in Table 5. can be seen when the curve is linear, the effect of characteristics on willingness to pay is significant, while when the curve is quadratic and limited by the 1st knot is non-significant, meaning there is no difference between regime 1 and regime 2. However, when limited by the 2nd knot, there is a significant effect, which means there is no difference between Regime 1 and Regime 2, but there is a difference with Regime 3. So, it can be concluded that there is a significant influence between characters on willingness to pay.

3.7 Direct Effect of Character (X) to Fear of Paying Late (Y_2)

The direct effect of the variable Character (X) to Fear of Paying Late (Y_2) can be described as in **Figure 3**.

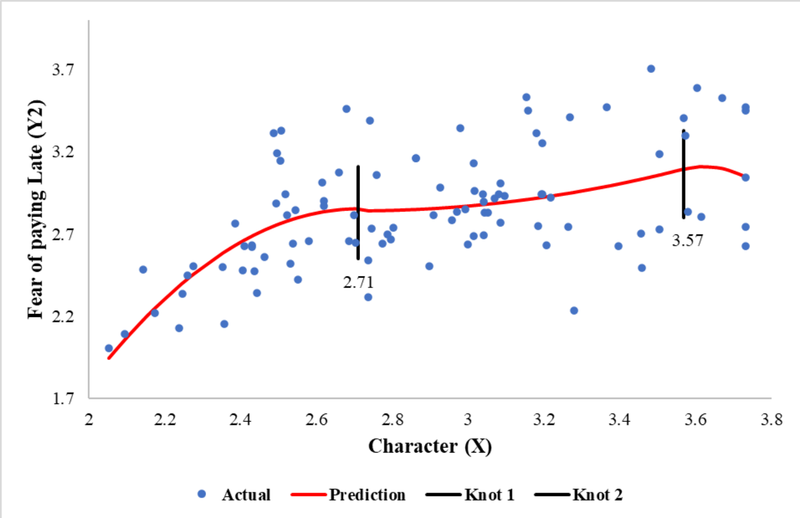

Figure 3. Direct effect X on Y_2

Testing the direct effect of Character (X) to Fear of Paying Late (Y_2) on the nonparametric truncated spline path model of quadratic polynomial degree (order p=2) with 2-knot points is divided into three regimes. When a character is less than 2.71, it has a slope of 2.13; between 2.71 and 3.57, it has a slope of 0.2, and more than 3.57, it has a slope of -0.79. In regime 1, the character increases with the fear of paying late. In regime 2, the slope value is close to 0, which tends to be constant. In regime 3, the slope is negative, meaning a decrease. This can be due to some mortgage debtor customers not being afraid of late payments because they already have savings to pay their obligations. In the results of hypothesis testing, all p-values are less than 0.05, which means significant. This indicates that there is a significant influence between Character (X) to Fear of Paying Late(Y_2).

3.8 Direct Effect of Character (X) to Obedient Paying Behavior (Y_3)

The direct effect of the variable Character (X) to Obedient Paying Behavior (Y_3) can be described as in **Figure 4**.

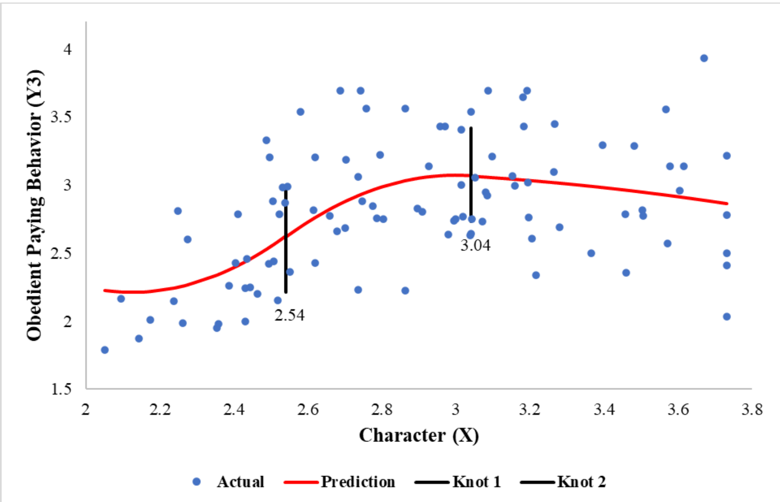

Figure 4. Direct effect X on Y_3

Testing the direct effect between Character (X) to Obedient Paying Behavior (Y_3) in the quadratic order truncated spline nonparametric path model with 2 knots is divided into three regimes. When a character is less than 2.54, the estimated line has a slope of 0.36, between 2.54 and 3.04 has a slope of 0.86, and more than 3.04 has a slope of -0.29. In regimes 1 and 2, character increases are accompanied by a rise in obedient paying behavior. Meanwhile, in regime 3, the slope is negative, meaning there is a decrease. Character is optimal when the category is good enough. This can be caused by the fact that sometimes, the better a person's character, the level of obedience will decrease because he feels he has done his best and has a high level of independence and self-confidence. In the results of hypothesis testing, all p-values are less than 0.05, which means significant. So that there is a significant influence between Character (X) on Obedient Paying Behavior (Y_3).

3.9 Direct Effect of Willingness to Pay (Y_1) to Obedient Paying Behavior (Y_3)

The direct effect of the variable Willingness to Pay (Y_1) to Obedient Paying Behavior (Y_3) can be described as in **Figure 5**.

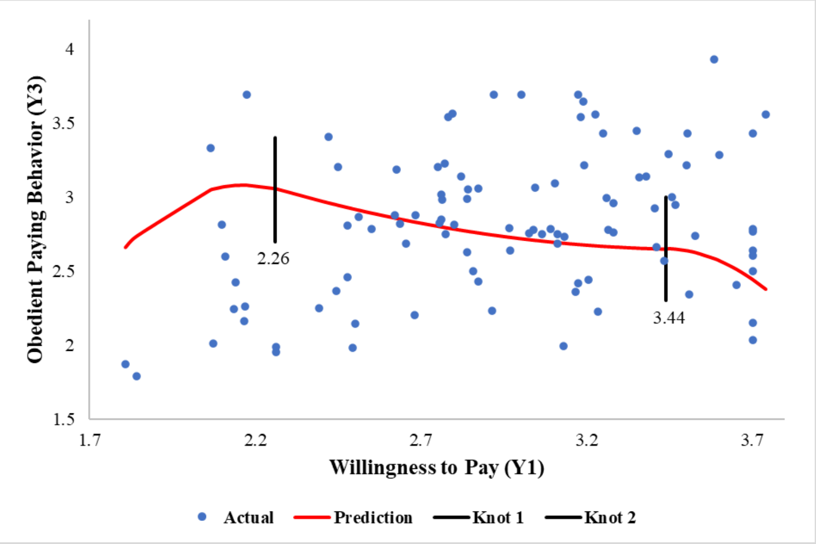

Figure 5. Direct effect Y_1 on Y_3

Testing the direct effect between Willingness to Pay (Y_1) to Obedient Paying Behavior (Y_3) on the nonparametric truncated spline path model of quadratic polynomial degree (order p = 2) with 2 knot points is divided into three regimes. When willingness to pay is less than 2.26 or in the low category, it has a slope of 1.09; between 2.26 and 3.44 has a slope of -0.42, and more than 3.44 has a slope of -0.96. Regime 1 shows an increased willingness to pay, accompanied by obedient paying behavior. Meanwhile, when the slope is negative in regime 2 and regime 3, there is a decrease. This means that having the willingness to pay is not necessarily obedient to pay, which can be caused by several factors, such as unstable financial conditions, administrative errors, and due to behavioral factors or habits that do not prioritize payment. In the hypothesis testing results, all p-values are less than 0.05, which means significant. This indicates that there is a significant influence between Willingness to Pay (Y_1) on Obedient Paying Behavior (Y_3). In this study, the effect between Willingness to Pay (Y_1) on Obedient Paying Behavior (Y_3) is a significant negative that tends to decrease in regime 2 and regime 3, shown from the graph that the higher the willingness to pay, the lower obedient paying behavior. In the graph above, it can be seen that the optimum point is when willingness to pay is not too high.

3.10 Direct Effect of Fear of Paying Late (Y_2) to Obedient Paying Behavior (Y_3)

The direct effect of variable Fear of Paying Late (Y_2) to Obedient Paying Behavior (Y_3) can be described as in Figure 6.

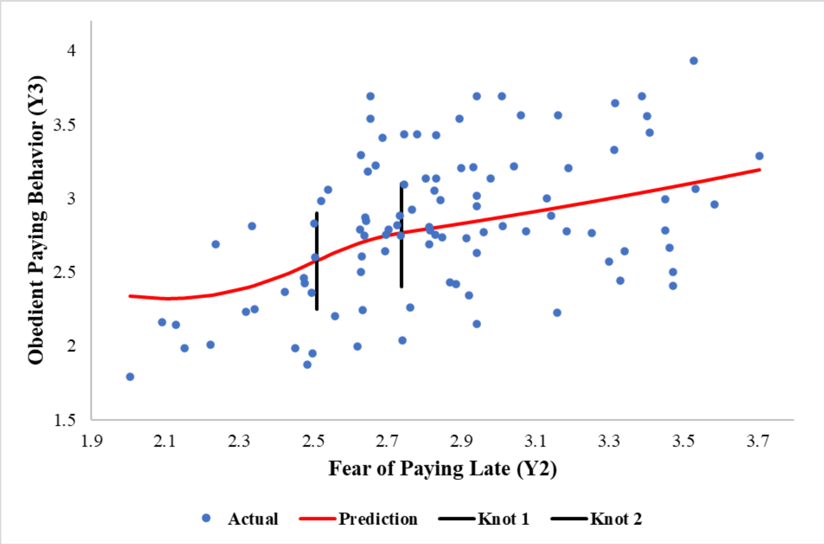

Figure 6. Direct effect Y_2 on Y_3

Testing the direct effect between Fear of Paying Late (Y_2) to Obedient Paying Behavior (Y_3) in the nonparametric truncated spline path model of quadratic polynomial degree (order p=2) with 2 knot points is divided into three regimes. When the fear of paying behavior is less than 2.51 or in the low category, the estimator line has a slope of -0.02. When the fear of paying behavior is between 2.51 and 2.74 or in the medium category, the estimator line has a slope of 0.93. Meanwhile, when the fear of paying late is more than 2.74 or in the good category, the estimation line has a slope of 0.45. Third, in regime 1, the slope is negative, which means there is a decrease; namely, when the fear of paying late increases, it will reduce obedient paying behavior. Meanwhile, regime 2 and Regime 3 show an increase, namely, an increase in fear of paying late will increase obedient paying behavior. This can be caused because the more afraid someone is to pay late, the more obedient that person is. The fear of paying late is a strong motivator for obedient paying behavior. The fear of financial consequences, such as credit score damage, tainted reputation, and social pressure, encourages individuals to fulfill their payment obligations on time. In the hypothesis testing results, the direct effect coefficients are positive and negative, and all p-values are less than 0.05, which means significant. This indicates that there is a significant influence between Fear of Paying Late (Y_2) on Obedient Paying Behavior (Y_3).

4. CONCLUSIONS

Based on the results of the analysis and discussion that has been carried out, the conclusions obtained are as follows:

1. The best nonparametric truncated spline path model is the quadratic polynomial order of 2 knots with a GCV value of 0.5588 and a coefficient of determination of 85.50%. This means that the model can explain 85.50% of the diversity of endogenous variables, and other factors outside the model explain the remaining 14.50%.
2. The significance of the best nonparametric truncated spline path in the banking credit of risk behavior model shows that all exogenous variables significantly affect endogenous variables.

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