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DEVELOPMENT OF NONPARAMETRIC PATH FUNCTION USING HYBRID TRUNCATED SPLINE AND KERNEL FOR MODELING WASTE-TO-ECONOMIC VALUE BEHAVIOR

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ABSTRACT

Waste management remains a challenge, including in Batu City, East Java, Indonesia. Rapid population growth and economic activities in the city have resulted in a substantial increase in waste volume. One of the key factors in solving waste problems is the mindset of the community towards waste management. The application of statistical analysis methods can be an effective approach to solving problems related to waste management from an economic point of view. Nonparametric path analysis is a statistical method that does not rely on the assumption that the curve is known. Nonparametric path analysis is performed if the data does not fulfill the linearity assumption. This study aims to determine the best nonparametric path function with a hybrid truncated spline and kernel approach among EV values of 0.5; 0.8; and 1. In addition, this study also aims to test the significance of the best path function obtained. The data used in this study are timer data obtained from the Featured Basic Research Grant. The results showed that the best model of hybrid truncated spline and kernel nonparametric path analysis is a hybrid model of truncated spline nonparametric path of linear polynomial degree 1 knot and kernel triangle nonparametric path at EV 0.5. In addition, the significance of the best nonparametric truncated spline and kernel hybrid path function estimation using jackknife resampling shows that all exogenous variables have a significant effect on endogenous variables as evidenced by a p-value smaller than (0.05).

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1. INTRODUCTION

Path analysis is a statistical method used to examine the direct and indirect effects of several variables, where some variables are considered as causal factors and other variables are considered as effects. According to [1], six assumptions that must be met in path analysis, one of which is that the relationship between variables is linear and additive. The linearity assumption is the first assumption that must be met before path analysis is performed. If the linearity assumption is met, then the suitable model is parametric path analysis. However, if the linearity assumption is not met, there are two possibilities. If the nonlinear form is known, then use nonlinear path analysis. However, if the nonlinearity is unknown and there is no information about the data pattern, then the analysis used is nonparametric path analysis [2].

Nonparametric path analysis is a statistical method that does not rely on the assumption that the shape of the curve is known, so the data has the freedom to determine the appropriate curve shape. One of the nonparametric approaches is spline. Truncated spline is one type of nonparametric regression model that can handle changing patterns at certain sub-intervals [3]. The advantage of a truncated spline is that it is good at handling data with sharply rising or falling patterns using knot points. Not only spline, but another nonparametric path approach is using kernel. The kernel nonparametric path can be used to estimate the conditional expected value of a random variable to find a nonlinear relationship between a pair of response and predictor random variables and obtain the appropriate weights. The data used in this study comes from the results of a questionnaire using a Likert scale that has been converted to an interval scale through the Summated Rating Scale (SRS) method. The characteristics of the data that are ordinal but converted to an interval scale are suitable for analysis with a nonparametric approach because nonparametric models can capture the flexibility of the relationship between variables that are not linear, which often occurs in social problems such as the waste economy. This method is appropriate because it can capture the complexity of relationships between variables that cannot be accommodated by conventional parametric approaches.

Analytical methods in statistics can be applied to solve everyday life problems such as the economic problem of waste, so this study will analyze the relationship between the influence of the variables of perceived benefits and perceived convenience on the behavior of converting waste into economic value mediated by the intention of changing people's mindset about waste. Various waste problems arise due to low public awareness of to disposal of waste in its place [4]. For example, throwing garbage in the river can pollute the water and block the flow of the river, which has the potential to cause flooding. In addition, the number of trash bins is still limited, especially in densely populated areas. Another problem is the increasing population and the growing rate of waste generation that continues to increase, while the availability of land and landfills is increasingly limited [5]. One way to develop a waste management system is to develop local and centralized management systems, including improving service operational patterns that include containerization, collection, transfer, transportation, and final disposal.

Problems with waste are still prevalent, as is the case in Batu City. Batu City is located in East Java Province, Indonesia. The rapid growth of population and economic activities in this city has led to a significant increase in waste volume. One of the main factors affecting the resolution of the waste problem is people's mindset towards waste. This mindset includes people's perspectives, attitude, and behavior towards waste. A poor mindset can make people not care about waste and dispose of it carelessly [6]. So far, people tend to view waste as something that is no longer useful or valuable. Therefore, this research was conducted to model the behavior of turning waste into economic value. Although the local government has been trying to manage waste through recycling programs and increasing public awareness, waste management infrastructure still needs to be improved [7].

The development of a nonparametric path function with a hybrid truncated spline and kernel approach has not been done by many researchers. Research by [8] examines the hybrid nonparametric path estimation model of the Fourier series and smoothing spline to produce a more flexible function estimate to approach the actual data pattern. From the study, it was found that the Fourier series and smoothing spline can be used in nonparametric path analysis only if the linearity assumption is violated. Another study was conducted by [9] which examined the method of developing a mixed nonparametric regression model of local polynomials and truncated spline, resulting in the finding that combined modeling between local polynomials and truncated spline produces a fairly complex model. However, this does not guarantee that the combined model is better than the simple model. Related research on the hybrid truncated spline and kernel nonparametric path analysis in the waste economy field is still rare in Indonesia. Therefore, based on the description above, the purpose of this study is to estimate the function and get the best model on the hybrid nonparametric truncated spline linear polynomial degree with 1-knot point and kernel triangle nonparametric path and determine the significance of the best function estimator in modeling the behaviour of converting waste into economic value through the jackknife resampling method.

2. RESEARCH METHODS

2.1 Research Data

The data used in this study is primary data obtained from a survey with a population of all people in Batu City, with a sample of 100 respondents. The research was conducted using latent variables derived from the Likert measurement scale. On this scale, there is a distance between one's attitude, for example strongly agreeing to disagreeing. The table of research variables and their measuring indicators can be seen in **Table 1**.

Table 1. Research Variables and Measurement Indicators

Variables	Indicator
Perceived Benefits (X_1)	Economic Benefits
	Environmental Benefits
	Social Benefits
Perceived Ease (X_2)	Ease of Access
	Ease of Process
	Ease of Information
Intention to Change People's Mindset on Waste (Y_1)	Desire to Change Behavior
	Commitment to Participate
	Motivation to Educate Others
Behaviour to Turn Waste into Economic Value (Y_2)	Recycling Activities
	Use of Recycled Products
	Making products with economic value

2.2 Linearity Assumption

Ramsey RESET is used to test the form of the linearity relationship. Hypothesis testing is used in the Ramsey RESET linearity test with the following steps **[10]**.

H_0 : $\beta_2 = \beta_3 = 0$ vs

H_1 : there is at least one $\boldsymbol{\beta_k \neq 0; k = 2,3}$

a. Regress X_1 on Y_i and calculate the estimated value of the response variable $\hat{Y}_i$.

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} \tag{1}$$

Calculating the coefficient of determination (R^2) of the regression.

$$R_1^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \tag{2}$$

b. Regress X_1 and two additional predictor variables $\hat{Y}_i^2$ and $\hat{Y}_i^3$ on $\hat{Y}_i^*$ (new regression equation).

$$\hat{Y}_i^* = \hat{\beta}_0^* + \hat{\beta}_1^* X_{1i} + \hat{\beta}_2 \hat{Y}_i^2 + \hat{\beta}_3 \hat{Y}_i^3 \tag{3}$$

Calculating the coefficient of determination (R^2) as **Equation (2)**.

c. Perform linearity test between variables

$$\text{F Test Statistics} = \frac{(R_2^2 - R_1^2)/m}{(1 - R_2^2)/(n-k-1-m)} \sim F_{(m,n-k-1-m)} \tag{4}$$

d. The test statistic approximates the F distribution with m and (n-k-1-m) degrees of freedom. Reject $\boldsymbol{H_0}$ if the F test statistic > $\boldsymbol{F_{(m,n-k-1-m)}}$ or the p-value < α. Thus, it can be concluded that the relationship between variables is not linear.

2.3 Truncated Spline Nonparametric Regression Analysis

Nonparametric regression is used when the assumptions of parametric regression are not met, one of which is because the curve does not follow a linear, quadratic, and polynomial shape. Truncated spline has the advantage of handling data patterns that show sharp changes, either in the form of increases or decreases, by using knot points, which are intersection points that show changes in data behavior patterns [11]. The truncated spline nonparametric regression model is as follows.

$$\hat{f}(X_i) = \hat{\beta}_0 + \sum_{j=1}^{p} \hat{\beta}_j X_i^j + \sum_{k=1}^{K} \hat{\beta}_k \left(X_i - K_k\right)_+^p \tag{5}$$

If **Equation (5)** is substituted into **Equation (6)**, the nonparametric spline regression equation in **Equation (7)** is obtained.

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki} + \varepsilon_i \tag{6}$$

$$Y_i = \beta_0 + \sum_{j=1}^{p} \beta_j X_i^j + \sum_{k=1}^{q} \beta_k \left(X_i - K_k\right)_+^p + \varepsilon_i \tag{7}$$

Where:

Y_i : The i-th response variable

X_i : The i-th predictor variable

K_k : The k-th knot point

i : $1,2,3,\ldots,n$, where n is the number of observations

j : $1,2,3,\ldots,p;\ p \geq 1$ with p is the order of the spline regression polynomials

k : $1,2,3,\ldots,K$ with K being the number of knot points

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

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

2.4 Truncated Spline Nonparametric Path Analysis

Parametric path analysis cannot be overcome when the regression curve is unknown and the linearity assumption is not met. Therefore, nonparametric path analysis was developed. The truncated spline nonparametric path analysis equation is as follows [12].

$$\underset{\sim}{Y} = \sum_{i=1}^{p} \underset{\sim}{f_i}(X_j) + \underset{\sim}{\varepsilon}; i = 1,2,\ldots,n; j = 1,2,\ldots,p \tag{8}$$

The truncated spline nonparametric path model when linear with 1 knot point for two exogenous variables and two endogenous variables are as follows:

$$\hat{f}_{1i} = \hat{\beta}_{10} + \hat{\beta}_{11} X_{1i} + \hat{\beta}_{12}(X_{1i} - K_{11})_+ + \hat{\beta}_{13} X_{2i} + \hat{\beta}_{14}(X_{2i} - K_{21})_+$$

$$\hat{f}_{2i} = \hat{\beta}_{20} + \hat{\beta}_{21} X_{1i} + \hat{\beta}_{22}(X_{1i} - K_{31})_+ + \hat{\beta}_{23} X_{2i} + \hat{\beta}_{24}(X_{2i} - K_{41})_+ + \hat{\beta}_{25} Y_{1i} + \hat{\beta}_{26}(Y_{1i} - K_{51})_+ \tag{9}$$

Where the truncated function:

$$\left(X_{1i}-K_{11}\right)_+=\begin{cases}\left(X_{1i}-K_{11}\right) & ;X_{1i}\geq K_{11}\\ 0 & ;X_{1i}<K_{11}\end{cases}$$

$$\left(X_{2i}-K_{21}\right)_+=\begin{cases}\left(X_{2i}-K_{21}\right) & ;X_{2i}\geq K_{21}\\ 0 & ;X_{2i}<K_{21}\end{cases}$$

$$\left(X_{1i}-K_{31}\right)_+=\begin{cases}\left(X_{1i}-K_{31}\right) & ;X_{1i}\geq K_{31}\\ 0 & ;X_{1i}<K_{31}\end{cases}$$

$$\left(X_{2i}-K_{41}\right)_+=\begin{cases}\left(X_{2i}-K_{41}\right) & ;X_{2i}\geq K_{41}\\ 0 & ;X_{2i}<K_{41}\end{cases}$$

$$\left(Y_{1i}-K_{51}\right)_+=\begin{cases}\left(Y_{1i}-K_{51}\right) & ;Y_{1i}\geq K_{51}\\ 0 & ;Y_{1i}<K_{51}\end{cases}$$

2.5 Kernel Nonparametric Path Analysis

Kernel regression is a nonparametric statistical technique used to estimate the conditional expectation of the response variable (Y) relative to an unknown function predictor variable and to obtain it appropriate weights are used. The kernel approach can be used to estimate the regression curve $\boldsymbol{f(X_i)}$ in kernel nonparametric regression. To obtain the kernel estimator, local polynomials are used **[13]**. First the regression curve $f(X_i)$ is approximated by a polynomial in the form as in **Equation (10)**.

$$f\left(X_i\right)=\alpha_0+\alpha_1\left(X_{1i}-X\right)^1+\ldots+\alpha_p\left(X_{1i}-X\right)^p+\varepsilon_i \tag{10}$$

p is the degree of the polynomial. The estimation of β is based on the weighted least squares method by minimizing as in **Equation (11)**.

$$\sum_{i=1}^{n}\varepsilon^2K_h\left(X_i-X\right)=\sum_{i=1}^{n}\left(Y_i-f\left(X_1\right)\right)^2\left(K_h\left(X_i-X\right)\right) \tag{11}$$

where X is the local point at the optimum bandwidth with minimum GCV and is the kernel weight.

The kernel nonparametric regression-based path analysis model is the development of kernel nonparametric regression analysis, with the kernel nonparametric path analysis function presented in **Equation (12)**.

$$\begin{aligned}\hat{Y}_{1i}&=\hat{\alpha}_{10}+\hat{\alpha}_{11}(X_{1i}-X)+\hat{\alpha}_{12}(X_{1i}-X)^2+\hat{\alpha}_{13}(X_{2i}-X)+\hat{\alpha}_{14}(X_{2i}-X)^2\\ \hat{Y}_{1i}&=\hat{\alpha}_{20}+\hat{\alpha}_{21}(X_{1i}-X)+\hat{\alpha}_{22}(X_{1i}-X)^2+\hat{\alpha}_{23}(X_{2i}-X)+\hat{\alpha}_{24}(X_{2i}-X)^2\\ &\quad+\hat{\alpha}_{25}(Y_{1i}-Y)+\hat{\alpha}_{26}(Y_{1i}-Y)^2\end{aligned} \tag{12}$$

2.6 Combined Truncated Spline and Kernel Nonparametric Path Model

Combined Truncated Spline Semiparametric Path and Kernel Nonparametric Path Model

a. Condition 1 ($Y_{1\mathrm{i}}$ is Truncated Spline function and $Y_{2\mathrm{i}}$ is Kernel function)

$$\begin{aligned}\hat{f}_{1i}&=\hat{\beta}_{10}+\hat{\beta}_{11}X_{1i}+\hat{\beta}_{12}(X_{1i}-K_{11})_++\hat{\beta}_{13}X_{2i}+\hat{\beta}_{14}(X_{2i}-K_{21})_+\\ \hat{f}_{2i}&=\hat{\alpha}_{20}+\hat{\alpha}_{21}(X_{1i}-X)+\hat{\alpha}_{22}(X_{1i}-X)^2+\hat{\alpha}_{23}(X_{2i}-X)+\hat{\alpha}_{24}(X_{2i}-X)^2\\ &\quad+\hat{\alpha}_{25}(Y_{1i}-Y)+\hat{\alpha}_{26}(Y_{1i}-Y)^2\end{aligned} \tag{13}$$

b. Condition 2 ($Y_{1\mathrm{i}}$ is Kernel function and $Y_{2\mathrm{i}}$ is Truncated Spline function)

$$\begin{aligned}\hat{f}_{1i}&=\hat{\alpha}_{10}+\hat{\alpha}_{11}(X_{1i}-X)+\hat{\alpha}_{12}(X_{1i}-X)^2+\hat{\alpha}_{13}(X_{2i}-X)+\hat{\alpha}_{14}(X_{2i}-X)^2\\ \hat{f}_{2i}&=\hat{\beta}_{20}+\hat{\beta}_{21}X_{1i}+\hat{\beta}_{22}(X_{1i}-K_{31})_++\hat{\beta}_{23}X_{2i}+\hat{\beta}_{24}(X_{2i}-K_{41})_+\\ &\quad+\hat{\beta}_{25}Y_{1i}+\hat{\beta}_{26}(Y_{1i}-K_{51})_+^2\end{aligned} \tag{14}$$

2.7 Optimal Knot Point Selection

[14] Stating that the method used to determine the optimal knot is the Generalized Cross Validation (GCV) method. If the optimal knot point is obtained, the best spline function is obtained. The GCV formula is as follows.

$$GCV(\mathbf{K}) = \frac{MSE(\mathbf{K})}{\left[n^{-1}trace(\mathbf{I}-\mathbf{A}(\mathbf{K}))\right]^2} \tag{15}$$

Where $MSE(\mathbf{K}) = n^{-1}\sum_{i=1}^{n}(Y_i - Y_i)^2$ and $\mathbf{K}$ are knot points and matrix $\mathbf{A}(\mathbf{K})$ is obtained from:

$$\begin{aligned} \hat{\mathbf{Y}} &= \mathbf{A}(\mathbf{K})\mathbf{Y} \\ \mathbf{A}(\mathbf{K}) &= \hat{\mathbf{Y}}^{-1}\mathbf{Y} \\ A[\mathbf{K}] &= \mathbf{X}[\mathbf{K}]\left(\mathbf{X}[\mathbf{K}]^{\mathbf{T}}\mathbf{X}[\mathbf{K}]\right)^{-1}\mathbf{X}[\mathbf{K}]^{\mathbf{T}} \end{aligned}$$

2.8 Model Fit Measure

The coefficient of determination is a measure of the contribution of predictor variables to the response variable. The coefficient of determination is used to determine how much diversity can be explained by the model formed. According to [2], the coefficient of determination formula is as follows.

$$R^2 = 1 - \frac{\sum_{k=1}^{3}\sum_{i=1}^{n}(Y_{ki} - \hat{f}_{ki})^2}{\sum_{k=1}^{3}\sum_{i=1}^{n}(Y_{ki} - \bar{Y}_k)^2}; 0 \le R^2 \le 1 \tag{16}$$

Where:

R^2 : Total coefficient of determination

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

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

$\bar{Y}_k$: Average of endogenous variables

i : $1,2,\dots,n$ with n number of observations

2.9 Jackknife Resampling

The resampling method can be used to test the significance of the path coefficient. The application of resampling is used to estimate the standard error and confidence interval of the population parameters [15]. A simple resampling technique had been used long before the bootstrap method was discovered, namely jackknife resampling. In 1949 the jackknife method was first discovered by Quenouille which is used to estimate the bias of an estimator by removing some sample observations. The jackknife method is known as a resampling method without returns, so there is an intertwined relationship in each resampling process. The jackknife method can be used to construct the variance of an estimator [16]. According to [17] the jackknife method can be divided based on the amount of data removed into the jackknife. In WarpPLS 6 software, the algorithm of the jackknife resampling process is called delete one, which is done by removing one sample and repeating each sample until the last one. Suppose there is a sample $X = (x_1, x_2, \dots, x_n)$ and $\hat{\beta} = s(x)$ is an estimate of a parameter, which will then be tested using the t-test statistic.

2.10 Hypothesis Testing (Resampling)

Hypothesis testing uses t-test statistics, where parameter estimates and standard errors are obtained from jackknife resampling. Hypothesis testing with t-test statistics as follows [18].

$$t = \frac{\hat{\beta}_j}{SE_{\hat{\beta}_j}} \sim t_{n-1} \tag{17}$$

The hypothesis used for the test statistics in **Equation (17)** is as follows.

$H_0 : \beta_j = 0$

$H_1 : \beta_j \neq 0$

The test criteria, namely if the test statistic $t > t_{\alpha/2(n-1)}$ then H_0 is rejected, which means that there is a significant influence between exogenous variables on endogenous variables.

2.11 Research Methods

This study uses nonparametric path analysis with a hybrid approach of truncated spine and kernel. Before the analysis is carried out, first test the linearity assumption. If the linearity assumption is not met, there are two possibilities. If the nonlinear form is known, then use nonlinear path analysis. However, if the nonlinearity is unknown and there is no information about the data pattern, then the analysis used is nonparametric path analysis. The total sample size used in this study was 100 with variables of Perceived Benefit (X_1), Perceived Ease (X_2), Intention to Change People's Mindset on Waste (Y_1), and Behaviour to Turn Waste into Economic Value (Y_2). The path model is analyzed to determine the nonparametric path function with a hybrid approach of truncated spline and the best kernel between EV 0.5, 08, 1 and then testing the hypothesis of the best model with the t-test at the jackknife resampling stage. The software used in this research is R Studio. The research model can be seen in **Figure 1**.

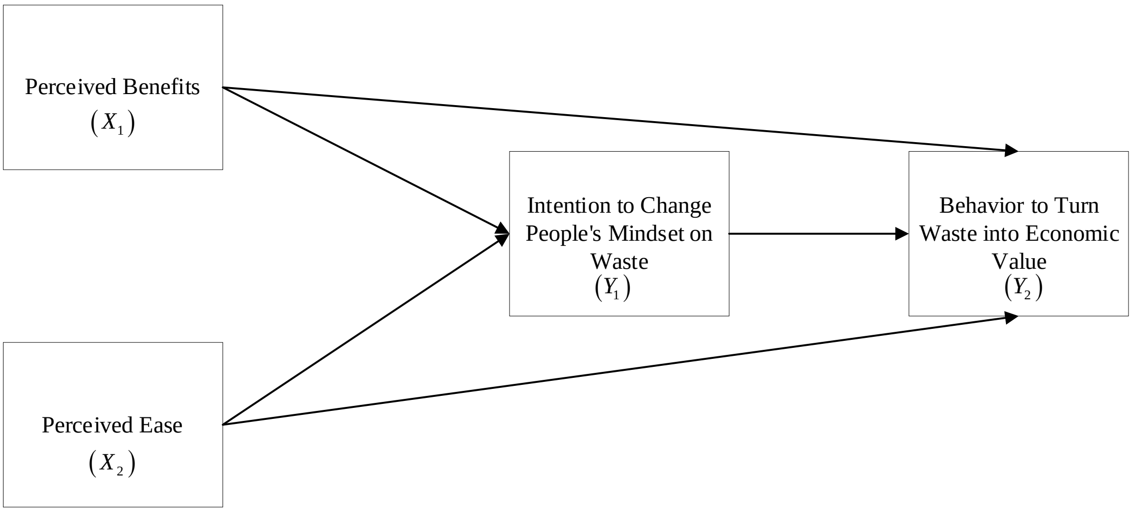

Figure 1. Research Model

The steps in this research are as follows:

a. Set the size of the observation value at (n=100).

b. Create a path diagram model consisting of two exogenous variables (X_1 and X_2) one mediation (Y_1) and one endogenous (Y_2).

c. Analyzing primary data to obtain path coefficients.

d. Path coefficient values from primary data for simulation data will be applied.

e. Assign exogenous variables (X) to follow uniform distribution using the minimum and maximum values of primary data, path coefficient values using primary data path coefficient values, residual values following multivariate normal distribution and endogenous variables formed based on **Equation (14)**.

f. Test the assumption of linearity of the relationship between variables using Ramsey's Regression Specification Error Test (RESET) with the F Test Statistic value.

g. Estimated coefficient values of the combined nonparametric path model of truncated spline linear order 1-knot point and kernel triangle nonparametric path analysis from the generation data. The relationship of X to Y_1 and Y_2 was estimated using nonparametric path analysis truncated spline linear order 1-knot point and nonparametric kernel triangle path analysis with various combinations of possible relationships from the five relationships contained in the research model.

h. In the nonparametric path analysis of the truncated spline of linear order 1-knot point and nonparametric path analysis of triangle kernel, the optimum model knot point and optimum bandwidth are selected based on the smallest GCV coefficient.

i. Determine the best model based on the largest coefficient of determination (R^2) value.

j. Through the prediction data results, the nonparametric path curve of the truncated spline of linear order 1-knot point and the nonparametric path analysis of kernel triangle on the best model was formed.

k. Hypothesis testing with t-test at the jackknife resampling stage on the best model in **Equation (17)**.

l. Interpretation of the best model obtained.

The scenario of the function estimation model on simulated data is designed to determine the combination of functions that are likely to be formed when combining Truncated Spline Nonparametric Path Analysis and Kernel Nonparametric Path Analysis.

$$Y_1 = f_1(X_1, X_2) + \varepsilon_1$$
$$Y_2 = f_2(X_1, X_2, Y_1) + \varepsilon_2$$
$$f_1(X_1, X_2) = f_{11}(X_1) + f_{12}(X_2)$$
$$f_2(X_1, X_2, Y_1) = f_{21}(X_1) + f_{22}(X_2) + f_{23}(Y_1)$$

Table 2. Scenario of Function Estimation Model on Simulated Data

No	Models	f_{11}	f_{12}	f_{21}	f_{22}	f_{23}
1	Combined Model of Truncated Spline and Kernel Nonparametric Path Analysis	TS	TS	TS	TS	K
2		TS	TS	TS	K	TS
3		TS	TS	TS	K	K
4		TS	TS	K	TS	TS
5		TS	TS	K	TS	K
6		TS	TS	K	K	TS
7		TS	TS	K	K	K
8		TS	K	TS	TS	TS
9		TS	K	TS	TS	K
10		TS	K	TS	K	TS
11		TS	K	TS	K	K
12		TS	K	K	TS	TS
13		TS	K	K	TS	K
14		TS	K	K	K	TS
15		TS	K	K	K	K
16		K	TS	TS	TS	TS
17		K	TS	TS	TS	K
18		K	TS	TS	K	TS
19		K	TS	TS	K	K
20		K	TS	K	TS	TS
21		K	TS	K	TS	K
22		K	TS	K	K	TS
23		K	TS	K	K	K
24		K	K	TS	TS	TS
25		K	K	TS	TS	K
26		K	K	TS	K	TS
27		K	K	TS	K	K
28		K	K	K	TS	TS
29		K	K	K	TS	K
30		K	K	K	K	TS

Description:
TS : Truncated Spline
K : Kernel

3. RESULTS AND DISCUSSION

3.1 Linearity Test of Relationship Between Variables

This study tests the linearity of each research model relationship using Ramsey's RESET test. The results of Ramsey's RESET test can be seen in **Table 3**.

Table 3. Linearity Assumption Test Results

Simulation Data	Variables	p-value	Results
EV=0.5	$X_1 \rightarrow Y_1$	0.011	Nonlinear
	$X_2 \rightarrow Y_1$	<0.001	Nonlinear
	$X_1 \rightarrow Y_2$	0.031	Nonlinear
	$X_2 \rightarrow Y_2$	<0.001	Nonlinear
	$Y_1 \rightarrow Y_2$	<0.001	Nonlinear
EV=0.8	$X_1 \rightarrow Y_1$	0.011	Nonlinear
	$X_2 \rightarrow Y_1$	<0.001	Nonlinear
	$X_1 \rightarrow Y_2$	0.031	Nonlinear
	$X_2 \rightarrow Y_2$	<0.001	Nonlinear
	$Y_1 \rightarrow Y_2$	<0.001	Nonlinear
EV=1	$X_1 \rightarrow Y_1$	0.011	Nonlinear
	$X_2 \rightarrow Y_1$	<0.001	Nonlinear
	$X_1 \rightarrow Y_2$	0.031	Nonlinear
	$X_2 \rightarrow Y_2$	<0.001	Nonlinear
	$Y_1 \rightarrow Y_2$	<0.001	Nonlinear

Based on **Table 3** it can be seen that the results of testing with Ramsey's RESET the relationship between exogenous and endogenous variables has p-value $< \alpha$ (0.05) with the hypothesis H_0 is rejected. Hence, the relationship between all variables is not linear.

3.2 Combined Results of Truncated Spline and Kernel Nonparametric Path Analysis

The combined Path Nonparametric Truncated Spline and Nonparametric Kernel on simulated data is reflected in **Table 4**.

Table 4. Combined Results of Truncated Spline Nonparametric Path and Kernel Nonparametric Path Simulated Data

No	f_{11}	f_{12}	f_{21}	f_{22}	f_{23}	R^2_{adj} EV 0.5	R^2_{adj} EV 0.8	R^2_{adj} EV 1
1	TS	TS	TS	TS	K	0.882	0.843	0.844
2	TS	TS	TS	K	TS	0.963	0.925	0.902
3	TS	TS	TS	K	K	0.886	0.844	0.846
4	TS	TS	K	TS	TS	0.908	0.900	0.876
5	TS	TS	K	TS	K	0.880	0.840	0.841
6	TS	TS	K	K	TS	0.902	0.894	0.870
7	TS	TS	K	K	K	0.873	0.830	0.832
8	TS	K	TS	TS	TS	0.897	0.889	0.865
9	TS	K	TS	TS	K	0.865	0.825	0.827
10	TS	K	TS	K	TS	0.891	0.883	0.859
11	TS	K	TS	K	K	0.861	0.818	0.819
12	TS	K	K	TS	TS	0.883	0.875	0.851
13	TS	K	K	TS	K	0.854	0.814	0.81
14	TS	K	K	K	TS	0.877	0.869	0.845
15	TS	K	K	K	K	0.848	0.804	0.805
16	K	TS	TS	TS	TS	0.873	0.866	0.842
17	K	TS	TS	TS	K	0.844	0.805	0.807
18	K	TS	TS	K	TS	0.867	0.859	0.836
19	K	TS	TS	K	K	0.838	0.795	0.797
20	K	TS	K	TS	TS	0.860	0.852	0.828
21	K	TS	K	TS	K	0.831	0.791	0.793
22	K	TS	K	K	TS	0.853	0.846	0.822
23	K	TS	K	K	K	0.824	0.781	0.783
24	K	K	TS	TS	TS	0.848	0.841	0.817
25	K	K	TS	TS	K	0.818	0.779	0.782
26	K	K	TS	K	TS	0.842	0.835	0.811

No	f_{11}	f_{12}	f_{21}	f_{22}	f_{23}	R^2_{adj} EV 0.5	R^2_{adj} EV 0.8	R^2_{adj} EV 1
27	K	K	TS	K	K	0.811	0.769	0.772
28	K	K	K	TS	TS	0.834	0.827	0.803
29	K	K	K	TS	K	0.804	0.765	0.768
30	K	K	K	K	TS	0.828	0.821	0.797

From the results of **Table 4**, it can be seen that the combined model of truncated spline nonparametric path and kernel nonparametric path on the best simulation data with R^2 of 0.963 on EV 0.5 simulation data. The best modeling results are the estimation of the combined function of the nonparametric path truncated spline and kernel nonparametric path with the relationship between X_1, X_2 to Y_1 modeled using truncated spline, the relationship between X_1 and Y_2 modeled with truncated spline, the relationship between $X_2$and Y_2 odeled with kernel, and the relationship between Y_1 and Y_2 modeled with truncated spline as follows.

$$\begin{aligned}\hat{f}_{1i} &= \hat{\beta}_{10} + \hat{\beta}_{11}X_{1i} + \hat{\beta}_{12}(X_{1i} - K_{11})_+ + \hat{\beta}_{13}X_{2i} + \hat{\beta}_{14}(X_{2i} - K_{21})_+ \\ \hat{f}_{2i} &= \hat{\beta}_{20} + \hat{\beta}_{21}X_{1i} + \hat{\beta}_{22}(X_{1i} - K_{31})_+ + \hat{\alpha}_{21}(X_{2i} - X) + \hat{\alpha}_{22}(X_{2i} - X)^2 + \hat{\beta}_{23}Y_{1i} + \hat{\beta}_{24}(Y_{1i} - K_{51})_+\end{aligned} \tag{18}$$

Estimation of Truncated Spline Nonparametric Path function and Simulated Kernel Nonparametric Path $EV = 0.5$.

$$\begin{aligned}\hat{f}_{1i} &= -0.439X_{1i} - 0.192(X_{1i} + 0.555)_+ - 0.196X_{2i} + 0.091(X_{2i} - 1.101)_+ \\ \hat{f}_{2i} &= 1.093X_{1i} - 0.447(X_{1i} - 0.497)_+ - 0.308(X_{2i} - 0.458) + 1.428(X_{2i} - 0.458)^2 \\ &\quad - 0.583Y_{1i} - 0.886(Y_{1i} - 0.452)_+\end{aligned} \tag{19}$$

Estimation of Truncated Spline Nonparametric Path function and Simulated Kernel Nonparametric Path $EV = 0.8$.

$$\begin{aligned}\hat{f}_{1i} &= -0.391X_{1i} - 0.237(X_{1i} + 0.429)_+ - 0.248X_{2i} + 0.106(X_{2i} - 1.101)_+ \\ \hat{f}_{2i} &= 1.360X_{1i} - 0.638(X_{1i} + 0.413)_+ - 0.245(X_{2i} - 0.458) + 1.419(X_{2i} - 0.458)^2 \\ &\quad - 0.127Y_{1i} - 1.712(Y_{1i} - 0.348)_+\end{aligned} \tag{20}$$

Estimation of Truncated Spline Nonparametric Path function and Simulated Kernel Nonparametric Path $EV = 1$.

$$\begin{aligned}\hat{f}_{1i} &= -0.288X_{1i} - 0.272(X_{1i} + 0.555)_+ - 0.335X_{2i} + 0.129(X_{2i} - 1.101)_+ \\ \hat{f}_{2i} &= 1.350X_{1i} - 0.573(X_{1i} + 0.512)_+ - 0.293(X_{2i} - 0.458) + 1.490(X_{2i} - 0.458)^2 \\ &\quad -0.628Y_{1i} - 0.942(Y_{1i} - 0.629)_+\end{aligned} \tag{21}$$

3.3 Model Feasibility Testing

The coefficient of determination aims to determine the ability of exogenous variables to explain endogenous variables. The coefficient of determination is between 0 and 1 where the model is getting better if the coefficient of determination is close to 1. The feasibility of the entire model is tested using the coefficient of determination, presented in **Table 5**.

Table 5. Coefficient of Determination of the Overall Model

Model	Simulation Data (EV)	R^2_{adj}
Combined Path Nonparametric Truncated Spline Linear 1 Knot and Path Nonparametric Kernel Triangle	0.5	0.963
	0.8	0.925
	1	0.902

Through **Table 5**, the combined truncated spline nonparametric path analysis and kernel nonparametric path analysis have a value of >0.75. Therefore, all analyses are categorized as good models. The selection of the best model is chosen through the largest coefficient of determination in each scenario, ease of interpretation, and the number of significant relationships between exogenous and endogenous variables.

The best model in this study was obtained through a combination of truncated spline nonparametric path analysis and kernel nonparametric path analysis with a sample size of 100 which resulted in a coefficient of determination of 0.963 or 96.3%. It can be interpreted that the variability of the behavioral variables of turning waste into economic value and the intention to change people's mindset about waste can be explained by the perceived usefulness and perceived convenience variables by 96.3%, while 3.7% is explained by other variables that are not used in the model.

3.4 Best Model Interpretation

Based on section 3.3, it is obtained that the best nonparametric combined path model of truncated spline linear 1 knot and kernel triangle is located at EV 0.5, which can be shown in **Equation (19)**. In addition to prediction, the combined truncated spline and kernel nonparametric path model can also be interpreted to determine the effect of exogenous variables on endogenous variables. Data patterns approximated by truncated spline nonparametric can be interpreted, while data patterns approximated by the kernel cannot be interpreted. The following is the interpretation of each variable.

a. Interpretation of the Effect of the Perceived Benefits variable on the Intention to Change the Public Mindset on Waste

Assuming that data other than perceived benefits are considered constant, the general model is obtained as follows.

$$\hat{f}_{1i} = \begin{cases} -0.439X_{1i} & ; X_{1i} < -0.555 \\ -0.106 - 0.631X_{1i} + c & ; X_{1i} \geq -0.555 \end{cases} \tag{22}$$

Based on **Equation (22)**, it can be interpreted that when perceived benefits are below -0.555, perceived benefits have a negative effect on the intention to change people's mindset about waste with an effect of 0.439. When the perceived benefits are more than -0.555, the perceived benefits have a negative effect on the intention to change people's mindset about waste with an effect of 0.631.

b. Interpretation of the Effect of the Perception of Ease variable on the Intention to Change the Public Mindset on Waste.

With the assumption that data other than perceived convenience is considered constant, the general model is obtained as follows.

$$\hat{f}_{1i} = \begin{cases} -0.196X_{2i} & ; X_{2i} < 1.101 \\ -0.1 - 0.105X_{2i} + c & ; X_{2i} \geq 1.101 \end{cases} \tag{23}$$

Based on **Equation (23)**, it can be interpreted that when the perception of convenience is below 1.101, the perception of convenience has a negative effect on the intention to change people's mindset about waste with an effect of 0.196. When the perception of convenience is more than 1.101, the perception of convenience has a negative effect on the intention to change people's mindset about waste with an effect of 0.105.

c. Interpretation of the Effect of the Perceived Benefits variable on the Behaviour of Turning Waste into Economic Value

Assuming that data other than perceived benefits are considered constant, the general model is obtained as follows.

$$\hat{f}_{2i} = \begin{cases} 1.093X_{1i} & ; X_{1i} < 0.497 \\ 0.222 + 0.646X_{1i} + c & ; X_{1i} \geq 0.497 \end{cases} \tag{24}$$

Based on **Equation (24)**, it can be interpreted that when the perception of benefits is below 0.497, the perception of benefits has a positive effect on the behaviour of converting waste into economic value with an effect of 1.093. When the perceived benefits are more than 0.497, the perceived benefits have a positive effect on the behaviour of converting waste into economic value with an effect of 0.646.

d. Interpretation of the Influence of the variable Intention to Change People's Mindset about Waste on Behaviour to Turn Waste into Economic Value

With the assumption that data other than the intention of changing people's mindset about waste is considered constant, the general model is obtained as follows.

$$\hat{f}_{2i} = \begin{cases} -0.583Y_{1i} & ;Y_{1i} < 0.452 \\ 0.44 - 1.469Y_{1i} + c & ;Y_{1i} \geq 0.452 \end{cases} \tag{25}$$

Based on **Equation (25)**, it can be interpreted that when the intention to change people's mindset about waste is below 0.452, the intention to change people's mindset about waste has a negative effect on behavior to turn waste into economic value with an effect of 0.583. When the intention to change people's mindset about waste is more than 0.452, the intention to change people's mindset about waste has a negative effect on the behavior of turning waste into economic value with an effect of 1.469.

3.5 Hypothesis Testing of the Best Model

Hypothesis testing using the t-test was carried out on the best model, namely the combined nonparametric truncated spline and nonparametric kernel triangle path model at $EV = 0.5$ through the jackknife method which began with jackknife resampling. Jackknife resampling in this study was carried out by removing two random observations at each resampling stage. Resampling is done 1000 times.

The hypothesis used is as follows.

$H_0 : \beta_j = 0$

$H_1 : \beta_j \neq 0$

Table 6. Best Model Hypothesis Testing Results

EV	Relationship	Function Estimator	Test Statistic t	p-value	Decision
0.5	$X_1 \rightarrow Y_1$	$\beta_{11}X_1$	14.62	<0.001	Significant
		$\beta_{12}(X_1 - K_{11})$	-15.15	<0.001	Significant
	$X_2 \rightarrow Y_1$	$\beta_{13}X_2$	8.84	<0.001	Significant
		$\beta_{14}(X_2 - K_{21})$	-23.65	<0.001	Significant
	$X_1 \rightarrow Y_2$	$\beta_{21}X_1$	-21.55	<0.001	Significant
		$\beta_{22}(X_1 - K_{31})$	-27.76	<0.001	Significant
	$X_2 \rightarrow Y_2$	$\alpha_{21}(X_2 - X)$	2.32	<0.001	Significant
		$\alpha_{22}(X_2 - X)^2$	-7.00	<0.001	Significant
	$Y_1 \rightarrow Y_2$	$\beta_{23}Y_1$	20.38	<0.001	Significant
		$\beta_{24}(Y_1 - K_{31})$	-22.83	<0.001	Significant
0.8	$X_1 \rightarrow Y_1$	$\beta_{11}X_1$	14.51	<0.001	Significant
		$\beta_{12}(X_1 - K_{11})$	-15.13	<0.001	Significant
	$X_2 \rightarrow Y_1$	$\beta_{13}X_2$	8.82	<0.001	Significant
		$\beta_{14}(X_2 - K_{21})$	-23.63	<0.001	Significant
	$X_1 \rightarrow Y_2$	$\beta_{21}X_1$	-21.58	<0.001	Significant
		$\beta_{22}(X_1 - K_{31})$	-27.73	<0.001	Significant
	$X_2 \rightarrow Y_2$	$\alpha_{21}(X_2 - X)$	2.38	<0.001	Significant
		$\alpha_{22}(X_2 - X)^2$	-7.08	<0.001	Significant
	$Y_1 \rightarrow Y_2$	$\beta_{23}Y_1$	20.33	<0.001	Significant
		$\beta_{24}(Y_1 - K_{31})$	-22.83	<0.001	Significant
1	$X_1 \rightarrow Y_1$	$\beta_{11}X_1$	14.65	<0.001	Significant
		$\beta_{12}(X_1 - K_{11})$	-15.16	<0.001	Significant
	$X_2 \rightarrow Y_1$	$\beta_{13}X_2$	8.87	<0.001	Significant
		$\beta_{14}(X_2 - K_{21})$	-23.61	<0.001	Significant
	$X_1 \rightarrow Y_2$	$\beta_{21}X_1$	-21.53	<0.001	Significant
		$\beta_{22}(X_1 - K_{31})$	-27.78	<0.001	Significant
	$X_2 \rightarrow Y_2$	$\alpha_{21}(X_2 - X)$	2.35	<0.001	Significant
		$\alpha_{22}(X_2 - X)^2$	-7.0	<0.001	Significant
	$Y_1 \rightarrow Y_2$	$\beta_{23}Y_1$	20.38	<0.001	Significant
		$\beta_{24}(Y_1 - K_{31})$	-22.83	<0.001	Significant

In **Table 6**. it can be seen that the p-value has a value less than (0.05), so it can be decided to reject H_0 in testing the hypothesis of each variable. So it can be concluded that the perceived benefit variable (X_1) affects the intention to change people's mindset about waste (Y_1), perceived convenience (X_2) affects the intention to change people's mindset about waste (Y_1), perceived benefit (X_1) affects the behavior of changing waste into economic value (Y_2), perceived convenience (X_2) affects the behavior of changing waste into economic value (Y_2), and the intention to change people's mindset about waste (Y_1) affects the behavior of changing waste into economic value (Y_2).

3.6 Discussion

The results of simulation studies using error variance (EV = 0.5, 0.8, and 1) show that error variance can affect the coefficient of determination of the model. The greater the error variance value used, the smaller the coefficient of determination. Overall, hypothesis testing with jackknife resampling of the combined model of nonparametric path truncated spline linear 1 knot and nonparametric path kernel triangle results in that there is a significant relationship between exogenous variables and endogenous research variables with various error variances (EV = 0.5, 0.8 and 1). Testing the feasibility of all models resulted in the best model with the largest coefficient of determination of 0.963, namely the combined nonparametric path truncated spline linear 1 knot and nonparametric path kernel triangle at EV 0.5. Thus, it can be concluded that the best scenario in the combined model of nonparametric path truncated spline linear 1 knot and nonparametric path kernel triangle is at EV 0.5.

4. CONCLUSIONS

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

a. The best model in estimating the combined function of the nonparametric truncated spline path with the nonparametric kernel triangle path is seen from the coefficient of determination of each model, which is 0.963, 0.925 and 0.902, respectively. So that the best model obtained is a combined nonparametric path truncated spline linear 1 knot with nonparametric path kernel triangle at EV 0.5, namely with the largest coefficient of determination value.

b. The results of hypothesis testing on the best model combined nonparametric path truncated spline linear 1 knot with nonparametric path kernel triangle at EV 0.5 using the t-test at the jackknife resampling stage obtained that the perceived benefit variable (X_1) affects the intention to change people's mindset about waste (Y_1), perception of ease (X_2) affects the intention to change people's mindset about waste (Y_1), perceived benefits (X_1) affects the behavior of changing waste into economic value (Y_2), perceived ease (X_2) affects the behavior of changing waste into economic value (Y_2), and the intention to change people's mindset about waste (Y_1) affects the behavior of changing waste into economic value (Y_2).

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