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Structural Equation Modeling Semiparametric Truncated Spline In Banking Credit Risk Behavior Models

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ABSTRACT

Housing is a fundamental need, and in Indonesia, the demand for housing has grown significantly alongside the population increase. Understanding factors that affect mortgage payment behavior is crucial for banks to ensure timely payments. This study examines the influence of customer attitudes on compliance behavior, fear of late payments, and payment punctuality among Home Ownership Credit (KPR) customers at Bank X. Using a semiparametric Structural Equation Modeling (SEM) approach, this study examines the relationship between these variables to understand better the factors that influence customer payment behavior. Findings reveal that positive customer attitudes significantly enhance compliant payment behavior (Y_1), reduce fear of late payments (Y_2), and increase payment punctuality (Y_3). Compliance behavior positively correlates with payment timeliness, while fear of late payments negatively influences payment punctuality, both relationships showing p-values below 0.001. These findings provide important implications for Bank X and the broader mortgage lending industry. These results suggest that fostering positive attitudes in mortgage customers may improve on-time payment behavior, contributing to the understanding of payment compliance in the field of mortgage lending.

Keywords: Character; Timeliness of Payments; Credit Customers; Semiparametric SEM; Truncated Splined

INTRODUCTION

Housing is a fundamental need, along with clothing and food. As Indonesia's population grows, the demand for housing has also increased significantly. The government, through various policies, aims to help citizens meet this need, one of which is through Home Ownership Credit (KPR), commonly known as Housing Loans [1]. KPR is a financing program offered by banks to assist individuals in buying or repairing homes with more affordable payment terms. Through KPR, customers can obtain a loan to own a home with scheduled installments [2].

In the banking sector, timely loan repayment is crucial as it affects a bank's reputation and credit performance. Successful management of customer credit performance directly impacts a bank's role in national development, profitability, and expansion into other services. In credit risk management, understanding factors influencing customer compliance in paying mortgage installments is essential, especially

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customer characteristics, which research indicates may affect compliance behaviors in non-linear ways [3]. According to previous studies, a customer's initially positive character traits may shift over time, leading to lapses in repayment compliance. This may result from various factors such as economic fluctuations, personal stress, or changing life priorities [4]. Consequently, customers who initially demonstrate good payment behavior may become less vigilant, increasing potential risks for banks.

Given the importance of understanding these dynamics, research on bank credit risk models that capture non-linear relationships between variables is relevant. Statistical modeling typically relies on three main approaches: parametric, nonparametric, and semiparametric. Parametric models are suitable when variable relationships are linear or well-defined [5], while nonparametric models are preferred when the relationship is unknown or non-linear [6]. Semiparametric models combine these approaches, addressing known linear relationships alongside non-linear, undetermined ones [7].

In nonparametric modeling, spline methods, specifically truncated splines, offer flexibility in capturing sharp shifts in data patterns. The use of splines in credit risk analysis helps capture non-linear relationships between customer characteristics and loan repayment behavior [8]. Previous studies have successfully applied truncated splines in longitudinal studies [9] and within the framework of nonparametric Structural Equation Modeling (SEM) [10]. Structural Equation Modeling (SEM) is a robust multivariate technique suited to complex relationships, particularly with latent variables. SEM involves an inner model for relationships between latent variables and an outer model for relationships between latent variables and their indicators [11]. A previous study by [12] developed a semiparametric SEM model using a truncated spline for first-order measurement models but only examined direct effects, without considering indirect or total effects.

In SEM analysis, the linearity assumption affects model structure, which can be tested using the Ramsey Regression Specification Error Test (RESET) [13]. Relationships within data can often be partly parametric and partly nonparametric. The study seeks to develop a semiparametric SEM model using a truncated spline approach to better capture the complexity of non-linear relationships in credit risk models, specifically how customer characteristics impact payment compliance.

State of the Art and Novelty while previous research has explored semiparametric SEM with direct effects, this study introduces the novelty of examining both indirect and total effects in a semiparametric SEM framework. This is expected to contribute significantly to credit risk modeling, providing a comprehensive understanding of indirect impacts and enhancing the theoretical framework in banking credit risk studies.

METHODS

Data

This study utilizes primary data collected through questionnaires as research instruments. The population targeted comprises mortgage customers at Bank X. Using a purposive sampling technique, a sample of 100 respondents was selected. The primary data collection was conducted through a questionnaire employing a Likert scale. This study examines one exogenous variable, Character (X_1); two intervening variables, Obedient Payment Behavior (Y_1) and Fear of Paying Late (Y_2); and one endogenous variable, Timely Payment (Y_3). The analysis method applied is semiparametric Structural Equation Modeling (SEM) truncated spline.

Research Model

The research model used can be seen in Figure 1.

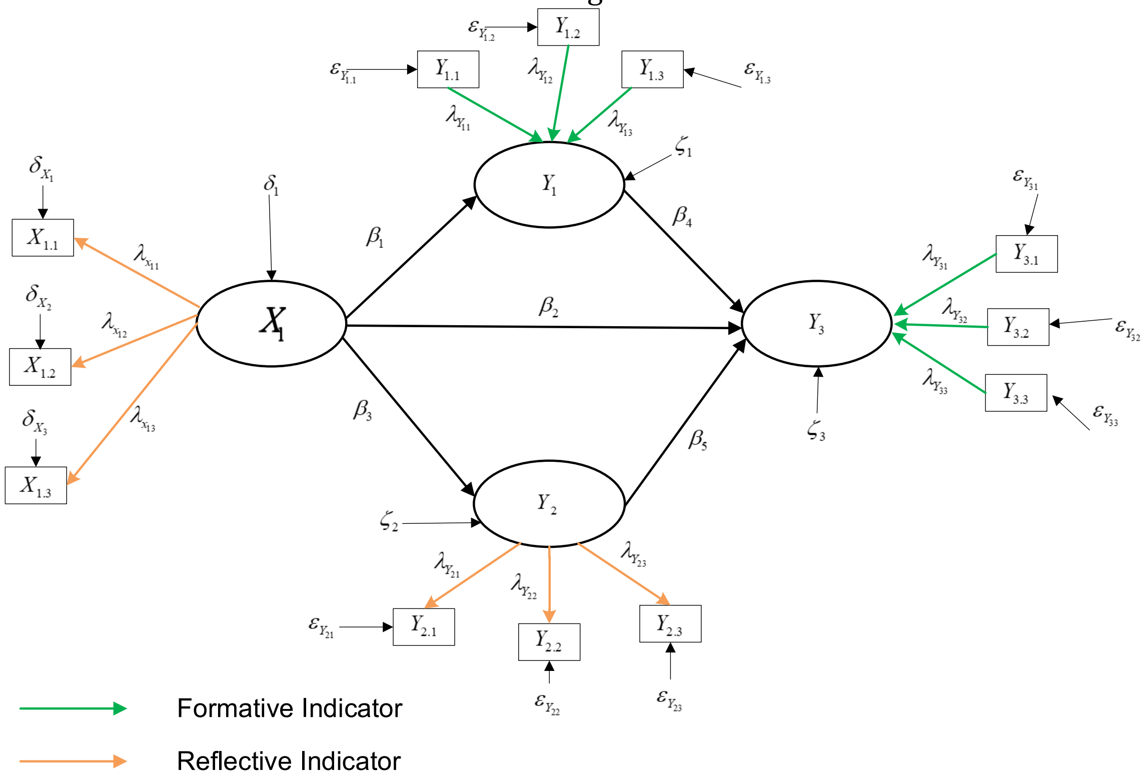

Figure 1. Research Model
Source: Processed by Researchers (2024)

Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is a type of multivariate analysis known for its capability to simultaneously analyze complex multivariate and multirelational data. SEM is commonly used to explore causal relationships between latent variables. It offers high flexibility by incorporating theoretical and empirical knowledge, modeling measurement errors, merging theory with empirical analysis, and validating hypotheses to support both theory confirmation and development [15].

Developed to address the limitations of commonly used statistical models, SEM includes elements of regression analysis, path analysis, and confirmatory factor analysis [16]. It is a technique that models simultaneous linear relationships among observed variables and incorporates latent variables, which are not directly measurable. SEM combines simultaneous equation systems, path analysis, regression analysis, and factor analysis to facilitate a comprehensive analytical approach [17].

Semiparametric SEM

Semiparametric structural models can be developed when some relationships can be known, and some forms are not yet known. In its development, more research has been needed on the semiparametric SEM approach using the truncated spline approach. The semiparametric structural model equation is basically similar to nonparametric path analysis, while the rest uses a parametric approach. Selecting knot points in the truncated spline model is a crucial step in semiparametric modeling, as it can significantly influence the fit and complexity of the model. One common approach for knot selection is using Generalized Cross-Validation (GCV), a method that balances model fit and complexity [18]. The semiparametric structural model equation is in Equation (1).

$$Y_{1i} = f_1(X_{1i}) + \zeta_{1i}$$
$$Y_{2i} = f_2(X_{1i}) + \zeta_{2i}$$
$$Y_{3i} = f_3(X_{1i}, Y_{1i}, Y_{2i}) + \zeta_{3i} \tag{1}$$

Description:

Y_{gk} : indicators for endogenous latent variables

$f_i(x_{ki})$: nonparametric regression function on the k-th exogenous variable of the i-th observation

ζ_g : Error term in the g-th model

According to Equation (1), the relationships between ($X_1 \rightarrow Y_1$) and ($X_1 \rightarrow Y_2$) uses a parametric approach, while the form of the relationship between ($X_1 \rightarrow Y_3$), ($Y_1 \rightarrow Y_3$) and ($Y \rightarrow Y_3$) uses a non-parametric approach. So it can be formed into Equation (2) and (3) which are semiparametric truncated spline linear SEM approaches with 1 knot and 2 knots:

$$\hat{y}_1 = \hat{\beta}_{01} + \hat{\beta}_{11} x_{1i}$$
$$\hat{y}_2 = \hat{\beta}_{02} + \hat{\beta}_{12} x_{1i}$$
$$\hat{y}_3 = \hat{\beta}_{03} + \hat{\beta}_{13} x_{1i} + \delta_{13}(x_{1i} - K_{11})_+ + \hat{\beta}_{23} y_{1i} + \delta_{23}(y_{1i} - K_{21})_+ + \hat{\beta}_{33} y_{2i} + \delta_{33}(\beta y_{2i1} - K_{31})_+ \tag{2}$$

$$\hat{y}_1 = \hat{\beta}_{01} + \hat{\beta}_{11} x_{1i}$$
$$\hat{y}_2 = \hat{\beta}_{02} + \hat{\beta}_{12} x_{1i}$$
$$\hat{y}_3 = \hat{\beta}_{03} + \hat{\beta}_{13} x_{1i} + \delta_{13}(x_{1i} - K_{11})_+ + \delta_{23}(x_{1i} - K_{12})_+ + \hat{\beta}_{23} y_{1i} + \delta_{33}(y_{1i} - K_{21})_+ + \delta_{43}(y_{1i} - K_{22})_+$$
$$+ \hat{\beta}_{33} y_{2i} + \delta_{53}(\beta y_{2i1} - K_{31})_+ + \delta_{63}(\beta y_{2i1} - K_{32})_+ + \zeta_3 \tag{3}$$

Description:

X_i : The i-th exogenous latent variable.

Y_g : The g-th endogenous latent variable.

β : The coefficient representing the influence of latent variables.

ζ_g : Error term in the g-th model

The semiparametric SEM approach in quadratic form with 1 knot and 2 knots can be presented in Equation (4) and (5).

$$\hat{y}_1 = \hat{\beta}_{01} + \hat{\beta}_{11} x_{1i}$$
$$\hat{y}_2 = \hat{\beta}_{02} + \hat{\beta}_{12} x_{1i}$$
$$\hat{y}_3 = \hat{\beta}_{03} + \hat{\beta}_{13} x_{1i} + \hat{\beta}_{23} x_{1i}^2 + \delta_{13}(x_{1i} - K_{11})_+^2 + \hat{\beta}_{33} y_{1i} + \hat{\beta}_{43} y_{1i}^2 + \delta_{23}(y_{1i} - K_{21})_+^2 + \hat{\beta}_{53} y_{2i} +$$
$$\hat{\beta}_{63} y_{2i}^2 + \delta_{33}(\beta y_{2i1} - K_{31})_+^2 \tag{4}$$

$$\hat{y}_1 = \hat{\beta}_{01} + \hat{\beta}_{11} x_{1i}$$
$$\hat{y}_2 = \hat{\beta}_{02} + \hat{\beta}_{12} x_{1i}$$
$$\hat{y}_3 = \hat{\beta}_{03} + \hat{\beta}_{13} x_{1i} + \hat{\beta}_{23} x_{1i}^2 + \delta_{13}(x_{1i} - K_{11})_+^2 + \delta_{23}(x_{1i} - K_{12})_+^2 + \hat{\beta}_{33} y_{1i} + \hat{\beta}_{43} y_{1i}^2 + \delta_{33}(y_{1i} - K_{21})_+^2 +$$
$$\delta_{43}(y_{1i} - K_{22})_+^2 + \hat{\beta}_{53} y_{2i} + \hat{\beta}_{63} y_{2i}^2 + \delta_{53}(\beta y_{2i1} - K_{31})_+^2 + \delta_{63}(\beta y_{2i1} - K_{32})_+^2 \tag{5}$$

RESULTS AND DISCUSSION

Linearity Test

The linearity test is used to determine the relationship between latent variables. The following are the results of the linearity test in Table 1.

Table 1. Linearity Test Results

Relationship	P-value	Decision
Character (X_1) → Payment Compliance Behavior (Y_1)	<0.001	Nonlinear
Character (X_1) → Fear of Paying Late (Y_2)	<0.001	Nonlinear
Character (X_1) → On time payment (Y_3)	<0.001	Nonlinear
Compliant Paying Behavior (Y_1) → Timely Paying (Y_3)	0.6163	Linear
Fear of Paying Late (Y_2) → Timely Paying (Y_3)	0.7095	Linear

Source: *Processed by Researchers (2024)*

The semiparametric SEM approach in quadratic form, with one and two knots, is represented in Equations (4) and (5). From the results in Table 1, it can be concluded that there is a non-linear relationship in the connections X_1 → Y_1, X_1 → Y_2, and X_1 → Y_3, as the null hypothesis (H_0) is accepted with a p-value less than 0.05. Meanwhile, the relationships Y_1 → Y_3 and Y_2 → Y_3 show a p-value greater than 0.05, leading to the rejection of H_0, which indicates linearity. The results indicate a mix of linear and non-linear relationships, as shown by the secondary data. The findings in Table 1 are illustrated by the data patterns presented in Figure 2 below.

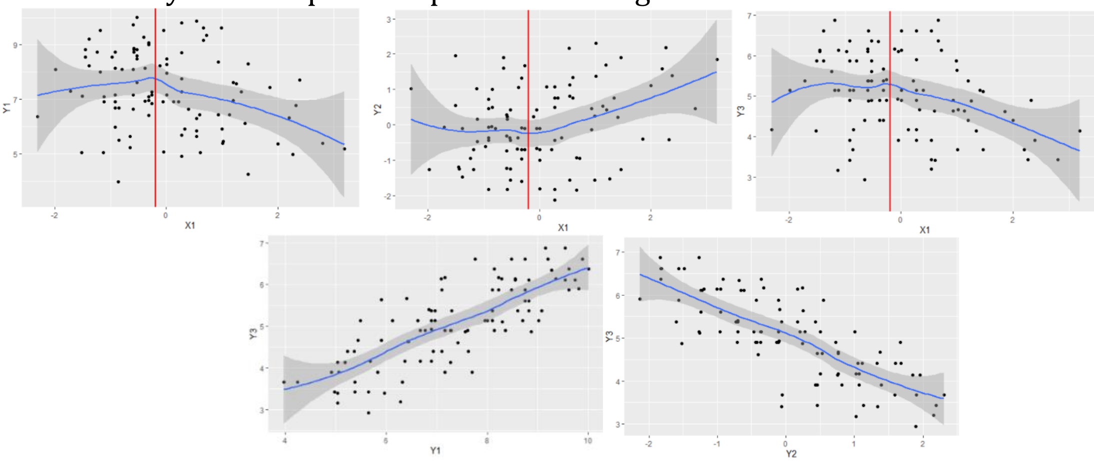

Figure 2. Curve Shape of Relationship Between Variables n Secondary Data
Source: *Processed by Researchers (2024)*

Figure 2 illustrates the curve shapes of relationships between variables in secondary data through a series of scatter plots, each complemented by a smooth trend line. The black dots in each subplot represent individual data points, showing the observed values of the variables. The blue lines indicate the fitted curves, likely generated using a smoothing technique such as splines, to capture the underlying relationship between the variables. The shaded gray areas around the trend lines represent confidence intervals, highlighting the uncertainty or variability of the fitted relationship. Vertical red lines in some subplots denote specific reference points, such as potential knot positions or threshold values, which might be critical in analyzing the relationships. These visualizations collectively provide insights into the patterns, linearity, or nonlinearity of associations between variables, aiding in the interpretation of the structural relationships in the data.

Measurement Model

In SEM analysis, two main models are used: the measurement model and the structural model. The initial stage in this study focuses on the outer model (measurement model). The SEM outer model consists of two types: reflective and formative models. Within the outer model, the outer loading value (for reflective indicators) and outer weight (for formative indicators) represent the contribution of each indicator in measuring the latent variable. The indicator with the highest outer loading or outer weight is considered the strongest or most dominant measure of the variable.

1. Character Variable Measurement Model (X_1)

The character variable (X_1) comprises three indicators. To examine the measurement model, the measurement weight values, and the p-values for each indicator of the character variable are presented in Table 2.

Table 2. Results of Loading Factor Variable Character (X_1)

Variables	Indicator	Measurement Model	Outer Loading	p-value
Character (X_1)	Cognitive component (X_{11})	Reflective	0.803	<0.001
	Affective component (X_{12})	Reflective	0.798	<0.001
	Behavioral component (X_{13})	Reflective	0.712	<0.001

Source: *Processed by Researchers (2024)*

As shown in Table 2, for the character variable (X_1), the strongest indicator is the Cognitive component (X_{11}), with an outer loading value of 0.803. The Affective component (X_{12}) is the second strongest indicator, with an outer loading value of 0.798, followed by the Behavioral component (X_{13}) in third position, with a loading value of 0.712. The p-values for all three indicators are <0.001, indicating that each indicator is significant in reflecting the character variable (X_1). The character of Bank X mortgage customers is most strongly influenced by the Cognitive component indicator (X_{11}).

1) Measurement model of the Paying Compliance Behavior variable (Y_1)

The Paying Compliance Behavior (Y_1) consists of three indicators. To analyze the measurement model, the measurement weight values and p-values for each indicator of Paying Compliance Behavior (Y_1) are presented in Table 3.

Table 3. Outer Weight Results of the Paying Compliance Behavior Variable (Y_1)

Variables	Indicator	Measurement Model	Outer Weight	p-value
Compliant Paying Behavior (Y_1)	Punctuality (Y_{11})	Formative	0.822	<0.001
	Data Accuracy (Y_{12})	Formative	0.730	<0.001
	Sanctions (Y_{13})	Formative	0.880	<0.001

Source: *Processed by Researchers (2024)*

As shown in Table 3, for the Paying Compliance Behavior variable (Y_1), the strongest indicator is Sanctions (Y_{13}), with an outer weight value of 0.880. The second strongest indicator is Timeliness (Y_{11}), with an outer weight value of 0.822, followed by Data Accuracy (Y_{12}) in third position, with an outer weight value of 0.730. The p-values for all three indicators are <0.001, indicating that each indicator is significant in forming the Paying Compliance Behavior variable (Y_1). The obedient payment behavior of Bank X mortgage customers is most strongly influenced by the Sanctions indicator (Y_{13}).

2) Measurement model of the Fear of Paying variable (Y_2)

The Fear of Paying variable (Y_2) has three indicators, to find out the measurement model, measurement weight value, and p-value of each indicator of the Fear of Paying variable (Y_2) is presented in Table 4.

Table 4. Outer Loading Results of the Sense of Paying Compliance Variable (Y_2)

Variables	Indicator	Measurement Model	Outer Weight	p-value
Fear of Paying (Y_2)	Physical Symptoms (Y_{21})	Reflective	0.762	<0.001
	Behavioral Symptoms (Y_{22})	Reflective	0.866	<0.001
	Cognitive Symptoms (Y_{23})	Reflective	0.813	<0.001

Source: *Processed by Researchers (2024)*

As shown in Table 4, for the Fear of Paying variable (Y_2), the strongest indicator is Behavioral Symptoms (Y_{22}), with an outer loading value of 0.866. The second strongest indicator is Cognitive Symptoms (Y_{23}), with an outer loading value of 0.813, followed by Physical Symptoms (Y_{21}) in third position, with an outer loading value of 0.762. The p-values for all three indicators are <0.001, indicating that each indicator is significant in reflecting the Fear of Paying variable (Y_2). The fear of paying among Bank X mortgage customers is most strongly influenced by the Behavioral Symptoms indicator (Y_{22}).

3) Measurement model of variable on time payment (Y_3)

The Timely Payment Behavior variable (Y_3) has two indicators, to find out the measurement model, measurement weight value, and p-value of each indicator of the Timely Payment variable (Y_3) is presented in Table 5.

Table 5. Outer Weight Results of the On-Time Payment Variable (Y_3)

Variables	Indicator	Measurement Model	Outer Weight	p-value
On Time Payments (Y_3)	Desire to Always Pay on Time (Y_{31})	Formative	0.857	<0.001
	Always Ontime Monthly Payment (Y_{32})	Formative	0.857	<0.001

Source: *Processed by Researchers (2024)*

As shown in Table 5, for the On-Time Payment variable (Y_3), the two strongest indicators are the desire to always pay on time (Y_{31}), with an outer weight value of 0.857, and Always on-time Monthly Payment (Y_{32}), with an outer weight value of 0.857. The p-values for both indicators are <0.001, indicating that both are significant in forming the On-Time Payment variable (Y_3). The on-time payment behavior of Bank X mortgage customers is most strongly influenced by these two indicators.

Direct Effect Test Results

The testing of the semiparametric SEM structural model, as depicted in Figure 2, reveals that the relationships between $X_1 \rightarrow Y_1$, $X_1 \rightarrow Y_2$, and $X_1 \rightarrow Y_3$ are non-linear. Additionally, the relationships between $Y_1 \rightarrow Y_3$ and $Y_2 \rightarrow Y_3$ also exhibit a non-linear pattern. The semiparametric SEM data analysis in this study is constrained to a linear form (order = 1) with one knot point, resulting in the following equation.

$$\hat{f}_1 = \hat{\beta}_{01} + \hat{\beta}_{11} x_{1i} + \delta_{11}(x_{1i} - K_{11})_+$$

$$\hat{f}_2 = \hat{\beta}_{02} + \hat{\beta}_{12} x_{1i} + \delta_{12}(x_{1i} - K_{11})_+$$

$$\hat{f}_3 = \hat{\beta}_{03} + \hat{\beta}_{13} x_{1i} + \delta_{12}(x_{1i} - K_{11})_+ + \hat{\beta}_{23} y_{1i} + \hat{\beta}_{43} y_{2i}$$

Based on the above equation, further analysis of Semiparametric SEM of direct effects with secondary data is presented in Table 6.

Table 6. Direct Effect Test Results

Relationship	Coefficient	Estimation	P-Value	Results
Character (X_1)→Payment Compliance Behavior (Y_1)	$\beta_1 x_1$	0.377	<0.001	Significant
	$\beta_1(x_1 - k_1)$	-0.804	<0.001	
Character (X_1)→Fear of Paying Late (Y_2)	$\beta_1 x_1$	-0.133	<0.001	Significant
	$\beta_1(x_1 - k_2)$	0551	<0.001	
Character (X_1)→On time payment (Y_3)	$\beta_1 x_1$	0.146	<0.001	Significant
	$\beta_1(x_1 - k_3)$	-0.386	<0.001	
Compliant Paying Behavior (Y_1)→Timely Paying (Y_3)	$\beta_1 y_1$	0.236	<0.001	Significant
Fear of Paying Late (Y_2)→ Timely Paying (Y_3)	$\beta_1 y_2$	-0.269	<0.001	Significant

Source: *Processed by Researchers (2024)*

Based on Table 6, the interpretation of the direct effect is as follows.

1) The direct effect of Character (X_1) on Paying Compliance Behavior (Y_1)

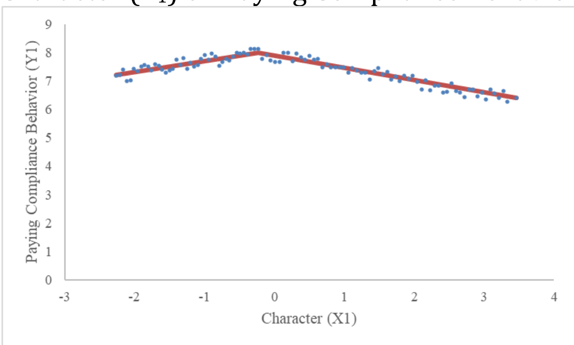

Figure 3. Direct Effect of X_1 on Y_1
Source: *Processed by Researchers (2024)*

In this study, testing the direct effect between character (X_1) and compliance paying behavior (Y_1) shows two different regimes based on the Character variable (X_1). The first regime occurs when X_1 is less than Knot 1 (k_1), with a coefficient of -0.2371 (with a measurement model range of 35.4%). The second regime occurs when X_1 is greater than Knot 1. Both direct effect coefficients are significant with p-values less than 0.001, indicating a significant relationship between character (X_1) and compliance paying behavior (Y_1). The interpretation of the results, as seen in Table 6 and Figure 3, can be divided into two conditions: first, when Bank X mortgage customers have low to moderate character (0% to 35.4%), higher character leads to higher compliance in paying behavior (Y_1). On the other hand, when customers have moderate to high character (35.4% to 100%), higher character leads to lower compliance in paying behavior. This finding indicates that, in the Semiparametric SEM approach, the relationship between the variables can vary under different conditions, while the classic Parametric SEM model can only assess this relationship under a single condition. This result suggests that reduced payment compliance can occur when customers face financial difficulties, such as recently being laid off or having poor financial habits, where they may not fully consider the long-term consequences of mortgage payments.

2) Direct effect between Character (X_1) on Fear of Paying Late (Y_2)

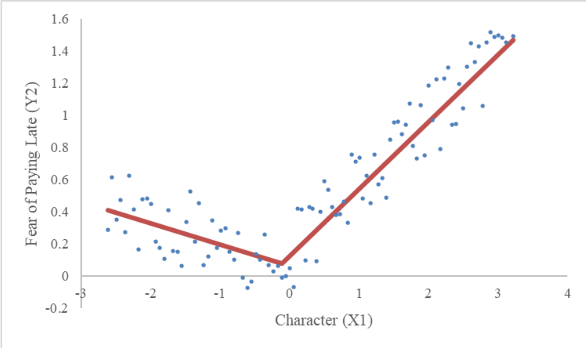

Figure 4. Direct Effect of X_1 on Y_2
Source: *Processed by Researchers (2024)*

The testing of the direct effect between Character (X_1) and Fear of Paying Late (Y_2) reveals two distinct regimes for the character variable (X_1). The first regime occurs when X_1 is less than Knot 2 (K_2), with a coefficient of -0.1093 (from the measurement model, the range is 43.0%). The second regime occurs when X_1 exceeds Knot 2. The analysis shows that both direct effect coefficients are significant with p-values less than 0.001, indicating a notable influence of Character (X_1) on Fear of Paying Late (Y_2). A comprehensive interpretation of the results, based on Table 6 and Figure 4, can be categorized into two conditions. First, for Bank X mortgage customers with low to moderate character (0% to 43%), an increase in character leads to a decrease in fear of paying late (Y_2). In the second condition, when customers possess higher character levels (above 43%), the relationship reverses, with a higher character leading to an increased fear of paying late. This dual influence observed in the Semiparametric SEM approach contrasts with the classic Parametric SEM model, which can only assess one condition at a time. The findings suggest that when Bank X mortgage customers struggle with managing their finances, an improvement in character can reduce their fear of late payments. However, when customers effectively manage their finances, a higher character may paradoxically increase their fear of late payments.

3) Testing the direct effect between Character (X_1) on On Time Payment (Y_3)

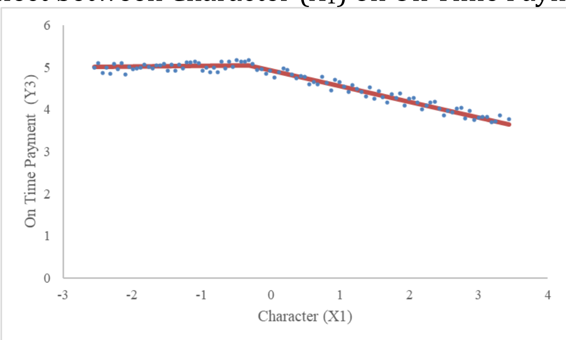

Figure 5. Direct Effect of X_1 on Y_3
Source: *Processed by Researchers (2024)*

The direct effect of Character (X_1) on Timely Payment (Y_3) in this study is tested under two distinct conditions based on the Character variable (X_1). The first regime occurs when X_1 is less than Knot 3 (K_3), with a coefficient of -0.3221 (within a range of 37.2% as per the measurement model). The second regime occurs when X_1 exceeds Knot 3. Both direct effect coefficients are significant, with p-values less than 0.001, indicating a substantial impact of Character (X_1) on Timely Payment (Y_3). A comprehensive interpretation of the two coefficients in Table 6 and the graph in Figure 5 leads to two interpretations. In the first condition, when Bank X mortgage customers have low to moderate character (ranging from 0% to 37.2%), an increase in character correlates with a higher likelihood of timely payment (Y_3). In contrast, in the second condition, when customers have moderate to high character (ranging from 37.2% to 100%), higher character levels lead to a decrease in timely payments. This suggests that for customers with lower to moderate character, improving their character enhances their timely payment behavior. However, for customers with higher character, excessive character may paradoxically reduce their sense of responsibility for making timely payments, as evidenced by the negative relationship between character and timely payment in the analysis.

4) Testing the direct effect between Compliant Paying Behavior (Y_1) on On Time Paying (Y_3)

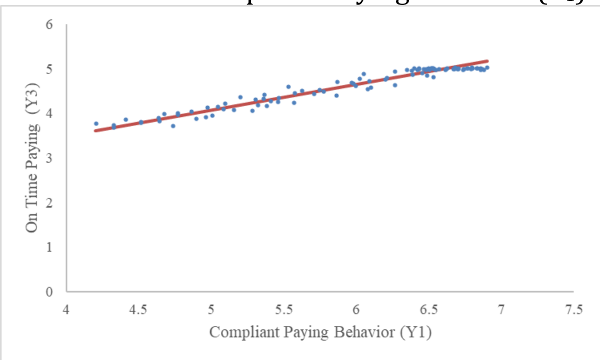

Figure 6. Direct Effect of Y_1 on Y_3
Source: *Processed by Researchers (2024)*

The direct effect of Compliant Paying Behavior (Y_1) on Timely Paying (Y_3) was tested and yielded a structural coefficient of 0.236 with a p-value of less than 0.001, indicating a significant relationship. This means there is a significant direct influence of Compliant Paying Behavior (Y_1) on Timely Paying (Y_3). The positive structural coefficient suggests that as Compliant Paying Behavior (Y_1) increases, Timely Paying (Y_3) among Bank X mortgage customers also increases.

5) Testing the direct effect between Fear of Paying Late (Y_2) on On Time Paying (Y_3)

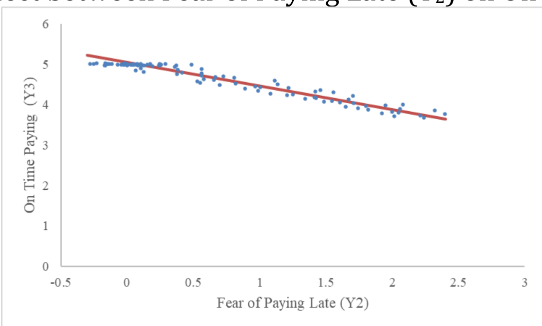

Figure 7. Direct Effect of Y_2 on Y_3
Source: *Processed by Researchers (2024)*

The direct effect of Fear of Paying Late (Y_2) on Timely Payment (Y_3) was tested, yielding a structural coefficient of -0.269 with a p-value of less than 0.001. Since the p-value is below 0.05, it indicates a significant direct effect between Fear of Paying Late (Y_2) and Timely Payment (Y_3). The negative structural coefficient suggests that as the Fear of Paying Late (Y_2) increases among Bank X mortgage customers, their Timely Payment (Y_2) tends to decrease.

The results of the direct effect in Table 6 if written using the following equation.

$$\hat{f}_1 = 8,081 + 0,377x_{1i} - 0,804(x_{1i} + 0,237)_+$$

$$\hat{f}_2 = 0,060 - 0,133x_{1i} + 0,551(x_{1i} + 0,109)_+$$

$$\hat{f}_3 = 5,043 + 0,236x_{1i} - 0,269(x_{1i} + 0,322)_+ + 0,236y_{1i} - 0,269y_{2i}$$

The measurement model results get a coefficient of determination of 0.9266. This can be explained that 92.66% of the diversity of variables Y_1 , Y_2 , and Y_3 can be explained by variable X_1 while 7.34% is explained by other variables that are not used in the model.

Testing Results of Indirect Influence

In addition to the direct effect, there is also an indirect effect between variables. There are two indirect effects, namely the first X_1 on Y_3 through Y_1. Second, the effect of X_1 on Y_3 through Y_2. Indirect effects are analyzed with the help of Sobel test software, with the results can be seen in Figure 8 and Table 7.

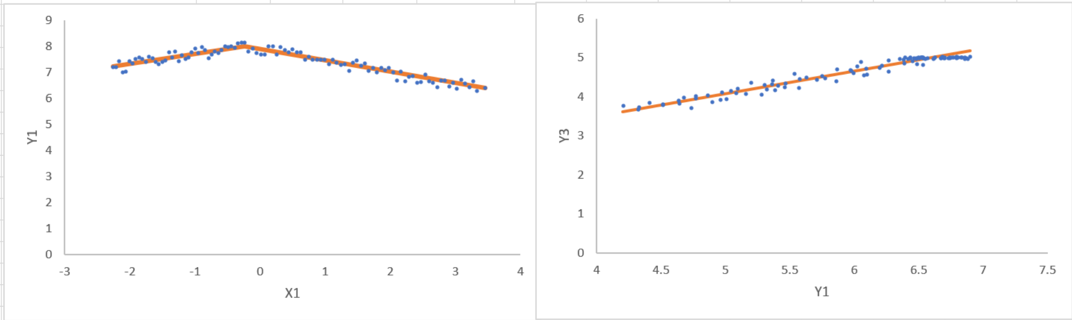

Figure 8. Indirect Influence Curve of Character (X_1) on Timely Payment (Y_3) through Compliance Payment Behavior (Y_1)

Source: *Processed by Researchers (2024)*

Based on Figure 8, the indirect effect of X_1 on Y_3 through Y_1 can be explained in two conditions. In the first condition, when the customer's charater ranges from 0% to 35.4%, the value of X_1 is 0.3770. However, when the character increases from 35.4% to 100%, the value of X_1 changes to -0.8044. The relationship between Y_1 and Y_3 remains at 0.2360. The indirect effect of X_1 on Y_3 through Y_1 yields a coefficient of -0.1898 with a p-value of less than 0.001, indicating a significant effect. These findings are summarized in Table 7.

Table 7. Results of the Indirect Influence of Character (X_1) on Timely Payment (Y_3) through Compliance Payment Behavior (Y_1)

X_1 on Y_3 through Y_1				
Condition 1: $X_1 <= K_1$				
Relationship	**Coefficient**	**Std Error**	***t-hit***	***P-value***
X_1 to Y_1	0.3770	0.0270		
Y_1 against Y_3	0.2360	0.0300		
X_1 on Y_3 through Y_1	0.0890	0.0130	6.8538	<0.001
Condition 2: $X_1 > K_1$				
X_1 to Y_1	-0.8044	0.0367		
Y_1 against Y_3	0.2360	0.0300		
X_1 on Y_3 through Y_1	-0.1898	0.0256	-7.4042	<0.001

Source: *Processed by Researchers (2024)*

The second indirect effect, namely Character (X_1) on On-Time Payment (Y_3) through Fear of Paying Late (Y_2) can be presented in Figure 9 and Table 8.

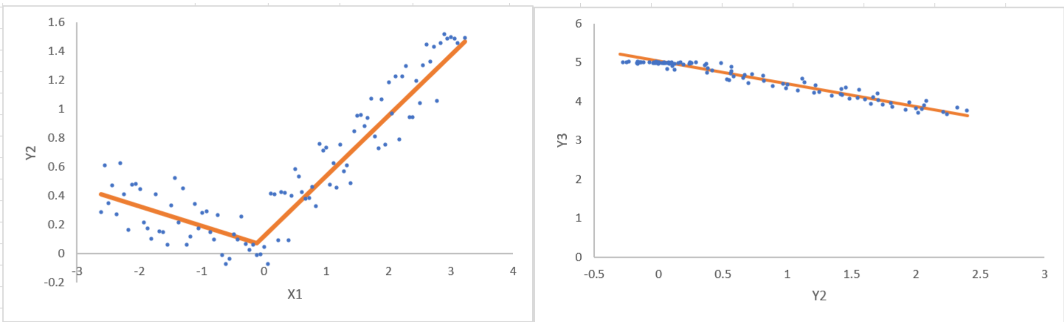

Figure 9. Indirect Influence Curve of Character (X_1) on Timely Payment (Y_3) Through Fear of Paying Late (Y_2)

Source: *Processed by Researchers (2024)*

Based on Figure 9, the indirect effect can be explained in two conditions. The first condition describes the relationship when X_1 is less than or equal to K_1 (the knot point, which marks a change in the curve behavior). The second condition explains the relationship when X_1 is greater than K_1. The analysis results of the indirect effects are presented in Table 8.

Table 8. Indirect Influence of Character (X_1) on Timely Payment (Y_3) Fear of Paying Late (Y_2)

X_1 on Y_3 through Y_2				
Condition 1: $X_1 <= K_2$				
Relationship	**Coefficient**	**Std Error**	***t-hit***	***P-value***
X_1 to Y_2	-0.1331	0.0244		
Y_2 against Y_3	0.2360	0.0300		
X_1 on Y_3 through Y_2	-0.0314	0.0070	-4.4862	<0.001
Condition 1: $X_1 > K_2$				
X_1 to Y_2	0.5509	0.0373		
Y_2 against Y_3	0.2360	0.0300		
X_1 on Y_3 through Y_2	0.1300	0.0187	6.9414	<0.001

Source: *Processed by Researchers (2024)*

The review of Table 8 reveals the results of the indirect effect between X_1 and Y_3 through Y_2 in two conditions. The first condition explains the effect of the character relationship when the customer's character is between 0% and 43%, while the second condition covers the relationship when the customer's character ranges from 44% to 100%. The results show that the relationship between a character score of 0% to 43% has a coefficient value of -0.1331. After reaching a point of 43% (K_2), the relationship between character scores from 44% to 100% increases, with a coefficient value of 0.5509. The relationship between Y_1 and Y_3 has a coefficient of 0.2360. Based on the direct effect results, the indirect effect of X_1 on Y_3 through Y_2 yields a coefficient of 0.1300 with a p-value <0.001, indicating a significant effect. These findings show that X_1 can influence Y_3 through Y_1.

Total Effect Test Results

Direct effect testing demonstrates the relationship between variables, while indirect effect testing reveals how the relationship between two variables can be mediated by other variables. Additionally, the total effect test is conducted to evaluate both the direct and indirect effects simultaneously. The results of the total effect analysis are shown in Table 9.

Table 9. Total Effect Test Results

Relationship	**Regime**	**Direct Influence**	**Indirect Effect**	**Total Influence**
X_1 to Y_1	$X_1 \leq k_1$	0.377*	-	0.377
	$X_1 > k_1$	-0.804*	-	-0.804
X_1 to Y_2	$X_1 \leq k_2$	-0.133*	-	-0.133
	$X_1 > k_2$	0.551*	-	0.551
X_1 to Y_3	$X_1 \leq k_3$	0.146*	Through Y_1 : 0.089*	0.235
	$X_1 > k_3$	-0.386*	Through Y_1 : -0.190*	-0.576
	$X_1 \leq k_3$	0.146*	Through Y_2 : -0.031*	0.115
	$X_1 > k_3$	-0.386*	Through Y_2 : 0.130*	-0.256
Y_1 against Y_3	-	0.236*	-	0.236
Y_2 against Y_3	-	-0.269*	-	-0.269

Notes: * Significant

Source: *Processed by Researchers (2024)*

Based on Table 9, the total effect calculation shows that the largest total effect occurs in the relationship between character (35.4% to 100%) and Compliance Paying Behavior (Y_1), with a negative coefficient of -0.804. The second largest total effect is observed in the relationship between character (37.2% to 100%) and Timely Payment (Y_3), with a negative coefficient of -0.576. The third largest total effect is found in the relationship between character (43% to 100%) and the Fear of Paying Late (Y_2), with a coefficient of 0.551. These results indicate that the second condition in each indirect effect plays a significant role in each relationship.

CONCLUSIONS

Based on the analysis and discussion conducted, it can be concluded that the semiparametric Structural Equation Modeling (SEM) approach provides significant insights into the relationships between variables. The results of the direct effects indicate that all relationships are statistically significant, as demonstrated by the derived functional equations. Furthermore, in the analysis of indirect and total effects, two conditions are identified: $X_1 \leq K_1$ and $X_1 > K_1$. Among these, the condition $X_1 > K_1$ emerges as the most influential, suggesting that the relationships and their effects intensify when X_1 surpasses the threshold K_1. This highlights the critical role of the knot point (K_1) in capturing changes in the strength and direction of variable interactions. The findings underscore the utility of the semiparametric SEM approach, particularly in accommodating non-linear relationships while preserving parametric interpretability, offering a robust framework for analyzing complex data structures. These results not only validate the model's effectiveness but also provide a comprehensive understanding of the dynamic interconnections among the studied variables.

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