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Comparison of Mediation Effects on Interaction and Multigroup Approach in Structural Equation Modeling PLS in Case of Bank Mortgage

Ulfah Maisaroh[1], Adji Achmad Rinaldo Fernandes[2], Atiek Iriany[3], Mohammad Ohid Ullah[4]
[1,2,3]Departement of Statistics, University of Brawijaya, Indonesia
[4]Departement of Statistics, Shahjalal Univeristy of Science and Technology, Bangladesh
ulfahmaisaroh@student.ub.ac.id[1], fernandes@ub.ac.id[2], atiekiriany@ub.ac.id[3], ohid-sta@sust.edu[4]

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ABSTRACT

Structural Equation Modeling is one of multivariate statistical method that used to explain multiple relationships between latent variables simultaneously to test a mediation model to conduct a formal test on mediation effects. Application PLS-SEM for exploratory research and theory development are increasing. Under certain conditions, the effect of exogenous variables on endogenous variable is also strengthened or weakened by moderating variable. In SEM, there are two approaches in analyzing moderation variables, namely the interaction method and the multigroup method. This article aims to compare the mediation effect on interaction approaches and multigroup approaches in Structural Equation Modeling. The data used is the case of timeliness of Bank X mortgage payments. In this article, statistical methods are evaluated to compare indirect effect between groups and examine indirect effect on each group. It was concluded that Collectability Status moderates the indirect relationship between Capital and the Timeliness of Payment through Willingness to Pay. Debtors with current collectability status more strongly effect the Timeliness of Payment than debtors with incurrect collectability status. Theresults of testing indirect effects on moderation with interaction and multigroup approaches are not much different. In the multigroup approach, the bootstrap interval bias is smaller than the bootstrap interval bias in the interaction approach. The Q-square Predictive Relevance value in both methods is quite high, indicating that the model is good. On the Current Collectibility Status group Q^2 is 89.3%, in the incurrect Collectibility Status Q^2 is 84.2%. While in the interaction approach, Q^2 is 70.4%. Researcher recommend a multigroup approach to data that has categorical moderation variables because differences between groups can be directly observed without adding interaction variables in the model.

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A. INTRODUCTION

Structural Equation Modeling (SEM) is commonly used to explain multiple relationships between latent variables simultaneously through visualization and validation of the model (Dash & Paul, 2021). Due to its adaptability and broad applicability, SEM has hugely popular in various fields (Mueller & Hancock, 2018). SEM is regarded as a method suitable for large samples. The sample size is commonly determined by three key factors: the distribution type of observed variables, the compolexity of the model, and the estimation method employed (Hayes, Montoya, & Rockwood, 2017). Alternatively, SEM is developed with a variance or component approach (Partial Least Square approach) (Annas, Ruliana, & Sanusi, 2022). Structural models use path analysis in analyzing effects between variables. As a development of path analysis, in SEM there are also direct effects and indirect effects. Direct effect is the effect of exogenous variables on endogenous variables without going through other variables as intermediaries. While indirect effect occurs when the effect of exogenous variables on endogenous variables requires other variables as intermediaries (mediation variables) (Solimun, 2010). In SEM, indirect effects are also often called mediating effects.

In addition to being accompanied by mediating variables as intermediaries, there are times when the effect of exogenous variables on endogenous variables is also strengthened or weakened by moderation variables. Moderation variables can be both nonmetric moderation and metric moderation (Hair J. F., Black, Babin, & Anderson, 2010). Nonmetric moderation is a categorical moderation variable that is usually grouped based on the characteristics of the variable. While metric moderation is a continuous moderation variable that can also be classified into groups based on desired categories (Hair J. F., Black, Babin, & Anderson, 2019). Mediation analysis is used when researchers attempt to understand, explain, or test hypotheses about how exogenous variables transmit their effect to endogenous variables through mediating (intermediate) variables. Moderation analysis is used when attention is directed to the question of when such effects occur. The integration between mediation analysis and moderation analysis is Conditional Process Analysis (Igartua & Hayes, 2021).

In some cases, the sample comes from two or more populations (Martens, et al., 2023). It is often an interesting question whether the effect of mediation is the same between different groups or under different conditions. Or can be said, whether the effect of mediation is moderated by another variable (moderation variable) that indicates a different group or condition (Ryu & Cheong, 2017). In structural equation modeling, there are two approaches in analyzing moderation variables, namely the interaction method and the multigroup method. In the interaction method, a categorical moderation variable is represented by a variable in the model. While the multigroup method uses categorical moderation variables to separate observations into groups, moderation variables do not appear in the model as variables.

With categorical moderation variables, moderated mediating effects are related to indirect effect differences between groups. For example (Levant, Parent, McCurdy, & Bradstreet, 2015) conducted a study and found that the mediating effect of masculinity ideological support on sleep disorder symptoms through the use of energy drinks differed significantly between white groups and racial minorities. Research by (Gelfand, et al., 2013) shows that the effect of cultural differences (United States vs. Taiwan) on the optimality of negotiation results is mediated by norms of alignment when negotiating as a team, but not when negotiating solo.

Another research using an interaction approach was conducted by (Tristanto, Nugraha, Waspada, Mayasari, & Kurniati, 2023) who examined the *Sustainability Performance Impact of Corporate Performance in Indonesia Banking*. The research resulted in the finding that institutional ownership moderates the indirect effect of sustainability on company performance through variable leverage. (Côté, Lauzier, & Stinglhamber, 2021) also conducted a study to evaluate work attachment in the relationship between presenteeism and job satisfaction by considering perceptions of organizational support as moderators. The research is presented in the form of a mediated moderation model and provides the result that perceived organizational support moderates the relationship between job attachment and job satisfaction, so that at low levels of job engagement, the feeling of being supported by the organization makes a difference to job satisfaction.

PLS-SEM is discussed as the preferred SEM method when the research objective is prediction (Hair, Hollingsworth, Randolph, & Chong, 2016). Application PLS-SEM for exploratory research and theory development are increasing. Recent releases of the SmartPLS software for executing multi-group analysis (Sarstedt, Henseler, & Ringle, 2011), invariance testing by means of the measurement invariance of composite models (Henseler, Ringle, & Sarstedt, 2016), linear and non-linear moderation, continuous moderators, confirmatory tetrad analysis (Gudergan, Ringle, Wende, & Will, 2008), and partial least squares prediction-oriented segmentation (PLS-OS) (Becker, Rai, Ringle, & Völckner, 2013).

The application of indirect effect analysis with moderation can be used in various fields, one of which is the banking sector. Banks as business entities that collect funds from the public in the form of deposits and distribute them in the form of loans or loans have credit distribution services, one of which is Home Ownership Loans. "From the consumer side, mortgage facilities are still the main choice in purchasing residential property with a share of 74.83% of total financing" (Komunikasi, 2023). Banks must be more careful in providing loans to prospective customers so as not to experience losses. The classification of mortgage customer installment payment status will be the focus of this study as a moderation variable. This classification is referred to as collectibility status which is divided into smooth and incurrent. A mortgage is a significant financial tool enabling individuals to purchase real estate using credit under specific terms and conditions (Lubis, Maulita, & Sihombing, 2023). In the banking and financial sector, having a comprehensive grasp of the characteristics of potential mortgage applicants is crucial.

Based on the explanation above, researcher is interested in identifying indirect effects on the case of punctuality of paying bank mortgages. In this article, the interaction method approach and multigroup method are presented in testing group differences on indirect effects using the Partial Least Square-Structural Equation Modeling (PLS-SEM). This research use the PLS-SEM approach because it was found that the PLS-SEM method provide better construct reliability and validity (Dash & Paul, 2021).

B. METHODS

1. Structural Equation Modeling

Structural Equation Modeling (SEM) is one of the multivariate statistical analysis methods in describing close linear relationships between observed variables that cannot be measured directly (latent variables) (Miftahuddin, Putri, Setiawan, & Oktari, 2022). In SEM, there are two models, namely the measurement model (outer model) and the structural model (inner model). The measurement model describes the model between the latent variable and its indicator. While the structural model describes the relationship or effect between latent variables (Hair J. F., Black, Babin, & Anderson, 2010). Alternatively, SEM is developed with a variance or component approach (PLS approach) (Annas, Ruliana, & Sanusi, 2022). Component-based SEM can analyze variables formed with reflective and formative indicators. Partial Least Square modeling has been widely used as a composite-based estimator to investigate models of structural equations with latent variables simultaneously in research (Cheah, Thurasamy, Memon, Chuah, & Ting, 2020). Formative measurement models are analyzed using Principal Component Analysis. In this model, it is as if latent variables affect the indicator. If the latent variable is an exogenous variable, then a formative measurement model is formulated in the Equation (1).

$$\boldsymbol{\xi = \lambda_1 x_1 + \lambda_2 x_2 + \cdots + \lambda_q x_q + \delta} \tag{1}$$

If the latent variable is an endogenous variable, then a formative measurement model is formulated in the Equation (2).

$$\boldsymbol{\eta = \lambda_1 y_1 + \lambda_2 y_2 + \cdots + \lambda_q y_q + \delta} \tag{2}$$

where $\boldsymbol{\xi}$ is an exogenous latent variable, $\boldsymbol{\eta}$ is an endogenous latent variable, $\boldsymbol{\lambda}$ is a weight coefficient $\boldsymbol{\xi}$ and $\boldsymbol{\eta}$, $\boldsymbol{\delta}$ and $\boldsymbol{\varepsilon}$ are errors. The SEM-PLS structural model is designed to represent the recursive model, which illustrates the causal relationships (casuality) between exogenous latent variables leading to endogenous latent variables. The formulation of the recursive model in PLS is presentes in Equation (3).

$$\boldsymbol{\eta_j = \beta_{ji}\eta_i + \gamma_{jb}\xi_b + \zeta_j} \tag{3}$$

where $\boldsymbol{\beta_{ji}}$ is the coefficient of the mediating endogenous variable path ji, $\boldsymbol{\gamma_{jb}}$ is the path coefficient of the exogenous variable jb, $\boldsymbol{\zeta_j}$ is the inner residual variable j, $\boldsymbol{\xi_b}$ is an exogenous latent variable b, and $\boldsymbol{\eta_j}$ pure endogenous latent variables.

2. Moderation Analysis on Indirect Effects

Indirect effect occurs when the relationship between exogenous variables (predictors or independents) to endogenous variables (respons or dependents) requires other variables as intermediaries (mediation). In general, indirect effect can be expressed as the product of two or more path coefficients, depending on the multiplicity of mediating variables between exogenous variables and endogenous variables (Chan, 2007). Moderation variables are variables that strengthen or weaken the effect of exogenous variables (predictors or independents) on endogenous variables (response or dependent) (Solimun, Fernandes, & Nurjannah, 2017). One important characteristic is that moderation variables are not effectd by exogenous variables. In structural equation modeling, there are two approaches in analyzing moderation variables, namely the interaction method and the multigroup method. In the interaction method, a categorical moderation variable is represented by a variable in the model. While the multigroup method uses categorical moderation variables to separate observations into groups, moderation variables do not appear in the model as variables. An illustration of a mediation-moderation model with interaction and multigroup approaches is illustrated in Figure 1.

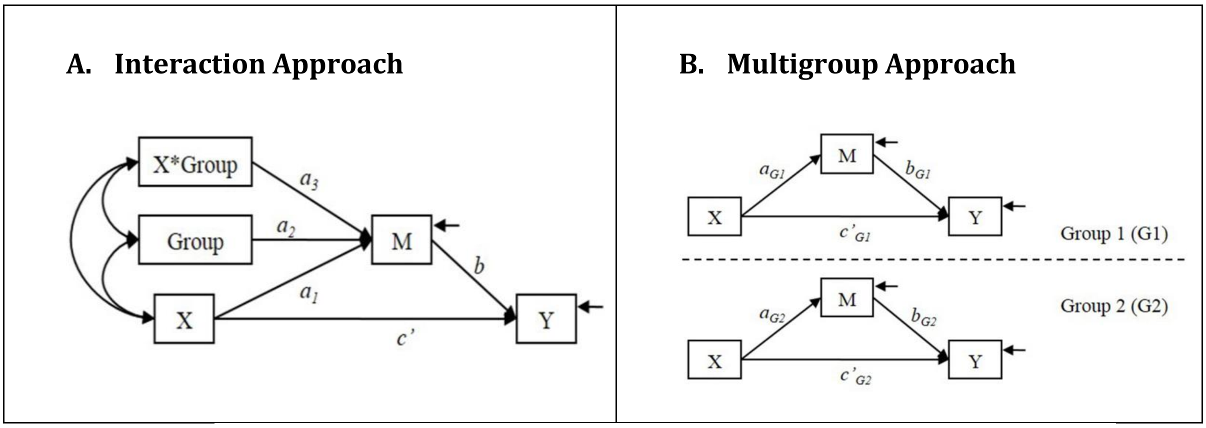

Figure 1. Moderation-Mediation Model of Interaction and Multigroup Approaches (Ryu & Cheong, 2017)

In moderation analysis using interaction approach, category variables that represent group membership are incorporated as covariates within the model. The term involving X and Group is introduced to examine the distinction between X and M. The interpretation of these parameters relies on the encoding of group membership. For example, if assign 1 for Group 1 , and 0 for Group 2, $a_1 =$ simple effect X to M in group 2; $a_2 =$ Conditional mean difference group M; $a_3 =$ difference in effect on M intergroup. If $a_3 = 0$, meaning the relationship of X and M differs between groups, the indirect effect of X on Y through M depends on group member. The estimated indirect effect X on Y through M is $[\hat{a}_1 + \hat{a}_3(Gruop)]\hat{b}$. Consequently, the estimation of the indirect effect on Group 1 is defined in Equation (4), and indirect effects on Group 2 formulated on the Equation (5).

$$[\hat{a}_1 + \hat{a}_3(1)]\hat{b} = [\hat{a}_1 + \hat{a}_3]\hat{b} \tag{4}$$

$$[\hat{a}_1 + \hat{a}_3(0)]\hat{b} = \hat{a}_1\hat{b} \tag{5}$$

The estimation of group differences in indirect effect is formulated in the Equation (6) (Hayes, An Index and Test of Linear Moderated Mediation, 2015).

$$\left[(\hat{a}_1 + \hat{a}_3)\hat{b}\right] - \hat{a}_1\hat{b} = \hat{a}_3\hat{b} \tag{6}$$

In the multigroup approach, member of group is not used as a predictor variable in the model. Using a categorical approach for a moderator is suitable when the moderator is genuinely categorical, but it's not advisable to form groups through arbitrary classification of a continuous moderator (Rucker, McShane, & Preacher, 2015). Instead, a set of hypothesized models is determined and estimated simultaneously. Group differences in simple effect X on M (as estimated by a_3 in the interaction approach) are estimated by Equation (7).

$$(\hat{a}_{G1} - \hat{a}_{G2}) \tag{7}$$

Simple indirect effects are estimated by the Equation (8) for Group 1, and Equation (9) for Group 2.

$$\left(\hat{a}_{G1}\hat{b}_{G1}\right) \tag{8}$$

$$\left(\hat{a}_{G2}\hat{b}_{G2}\right) \tag{9}$$

The estimation of the difference in indirect effect is presented in the Equation (10).

$$\left(\hat{a}_{G1}\hat{b}_{G1} - \hat{a}_{G2}\hat{b}_{G2}\right) \tag{10}$$

3. Bootstrap Method

The Bootstrap method is recommended to examine indirect influences on previous research conducted by (MacKinnon, Lockwood, & Williams, 2004) and (Preacher & Hayes, 2008). In the Bootstrap method, a large number of Bootstrap samples, which are the same size as the original sample size, are taken from the original sample by iteration. Estimates obtained in each Bootstrap sample (Ryu & Cheong, 2017). The sampling distribution is created using the set of 500 Bootstrap. From bootstrap sampling distribution, Bootstrap confidence interval percentile ($[100 \times (1-\alpha)]$) can be calculated by $(\alpha/2)$ and $(1-\alpha/2)$ percentiles. Bootstrap's confidence interval corrected bias can be calculated according to an adjusted percentile based on a lower proportion of bootstrap estimates than the original sample estimate. In analysis with an interaction approach, the estimate of indirect influence on each group is calculated by Equation (11) for Group 1 (code 1) and Equations (12) for Group 2 (code 0).

$$(\hat{a}_1^* + \hat{a}_3^*)\hat{b}^* \tag{11}$$

$$(\hat{a}_1^* + \hat{a}_3^*) \tag{12}$$

The * indicates that the estimate was obtained in the Bootstrap sample. In multigroup analysis, simple indirect influence estimation is calculated by Equation (13) for group 1, and Equation (14) for group 2.

$$\left(\hat{a}_{G1}^*\hat{b}_{G1}^*\right) \tag{13}$$

$$\left(\hat{a}_{G2}^*\hat{b}_{G2}^*\right) \tag{14}$$

4. Difference Test (Wald)

Mediation testing on the interaction approach can be do by looking at the *p-value* on the relationship between interaction variables to pure endogenous variables through mediation variables. “While the multigroup approach, the data is separated into sub-groups based on moderating variables, and the indirect effect is estimated on each group and compared between groups” (Ryu E. , 2015). The type of data used on moderator variables is category. The hypothesis can be written:

$$H_0: a_{(G_1)}b_{(G_1)} = a_{(G_2)}b_{(G_2)}$$
$$H_1: a_{(G_1)}b_{(G_1)} \neq a_{(G_2)}b_{(G_2)}$$

To examine the restrictions imposed by the equation $a_{(G_1)}b_{(G_1)} - a_{(G_2)}b_{(G_2)} = 0$, can employ the Wald test method, as proposed by (Bollen, 1989). The wald test statistics help assess the degree to which parameter estimates in the model deviate from zero, while accounting for sampling error. Wald's statistics are obtained by Equation (15)

$$W = \frac{\hat{\theta}_1^2}{avar(\hat{\theta}_1)} \tag{15}$$

where $avar(\hat{\theta}_1)$ is an estimate of asymptotic variance of $\hat{\theta}_1$, with degree of freedom = 1. Equation (15) represents the square of the typical Z ratio used to assess the estimated significance of the parameter. As a result, W can be seen an extension of the standard Z test. In indirect effect testing between group 1 (G_1) with group 2 (G_2), $\hat{\theta}_1 = \hat{a}_{(G_1)}\hat{b}_{(G_1)} - \hat{a}_{(G_2)}\hat{b}_{(G_2)}$ and $avar(\hat{\theta}_1)$ Estimation of asymptotic variance $\left[\hat{a}_{(G_1)}\hat{b}_{(G_1)} - \hat{a}_{(G_2)}\hat{b}_{(G_2)}\right]$.

5. Goodness of Fit

The inner model is evaluated by looking at the percentage of variance explained by looking at R^2 for latent variables (Henseler & Sarstedt, 2013). Q-Square predivtive relevance measures how well conservation values are produced by the model as well as parameter estimation. The calculation of Q-square predictive relevance is done with the formula presented in the Equation (16).

$$Q^2 = 1 - (1 - R_1^2)(1 - R_2^2) \tag{16}$$

where R_1^2, R_2^2 is the coefficient of determination of endogenous variables in the model. Interpretation of Q^2 is same as the interpretation of the coefficient of total determination on path analysis. Q^2 has a value range $0 < Q^2 < 1$, where the closer to 1, the better the model.

6. Data and Variables

The data in this research is in the form of latent variables from the questionnaire, with respondents being customers of Bank X mortgage debtors. The number of samples used was 100 respondents. The scale used is the Likert scale. A full explanation of variables is presented in Table 1.

Table 1. Research Variables

Variable	Indicators
Capital (X)	Sources of steady income
	Have other business fields as a source of income
	Have savings of deposits in bank
Willingness to Pay (M)	Consultation
	Documents presented

	How and where to pay credit
	Payment deadline
	Fund Allocation
Timeliness of Pay (Y)	Wishes are always on time paying
	Always on time payment per month
Collectibility status (Group)	0: Incurrent 1: Current

7. Research Method and Research Model

The following is a flow chart that shows the research method presented explicitly in Figure 2.

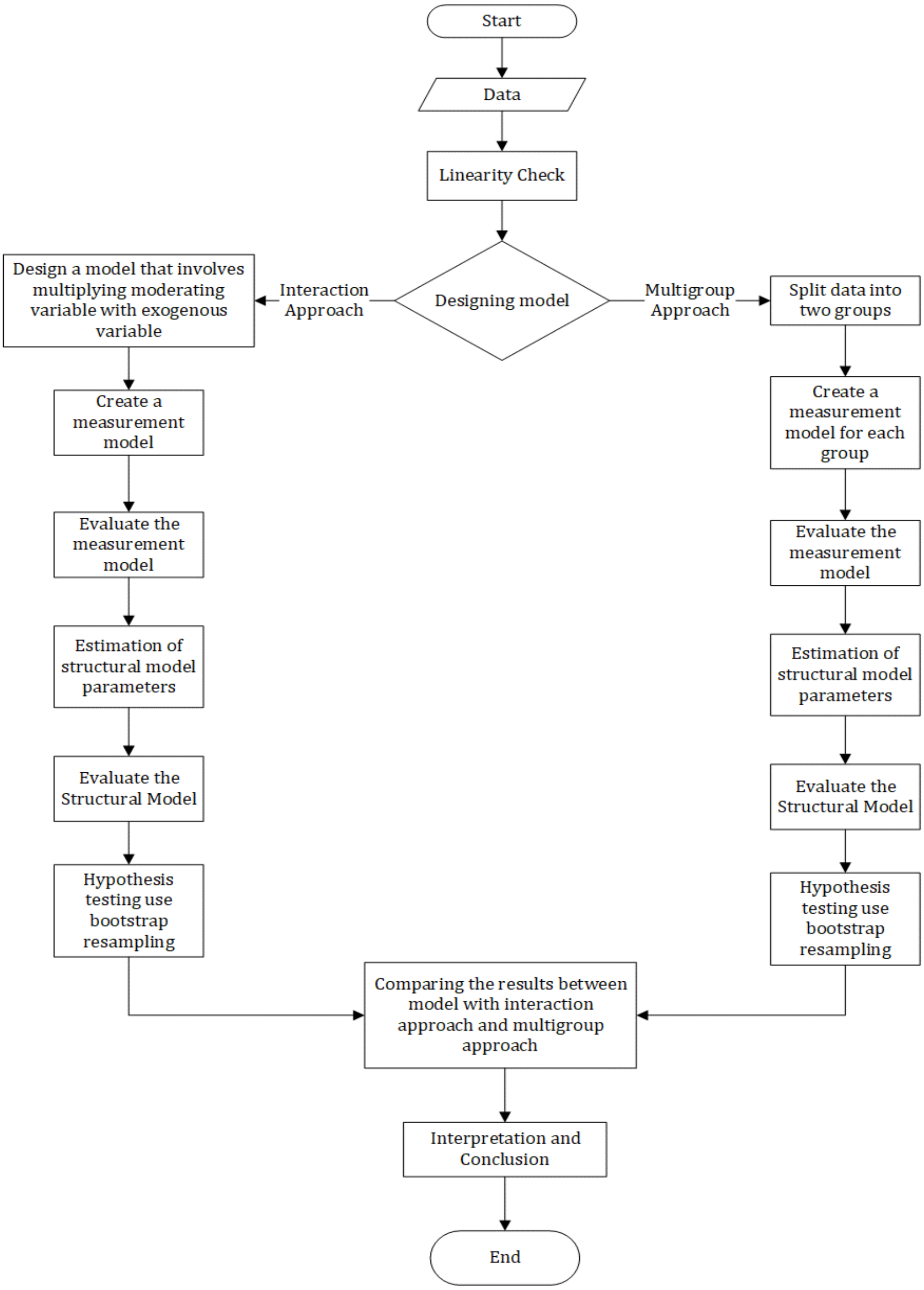

Figure 2. Flowchart

This study compares two approaches in the analysis of indirect effect moderation, namely the interaction approach and the multigroup approach. Therefore, there are two research models presented in Figure 3 and Figure 4.

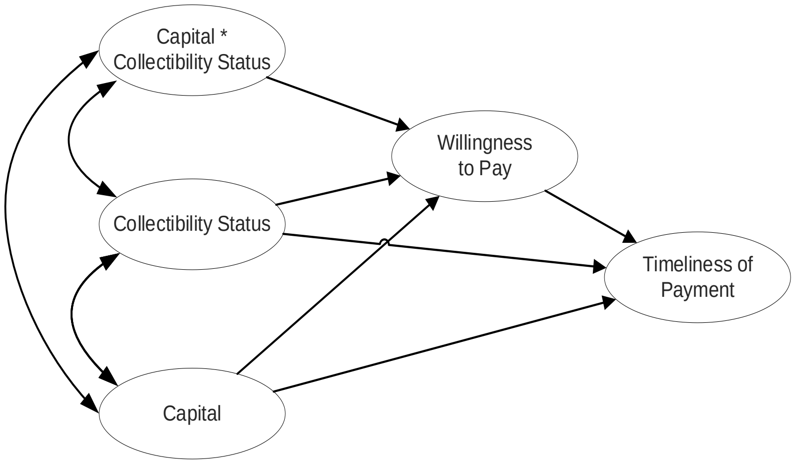

Figure 3. Research Model Interaction Approach

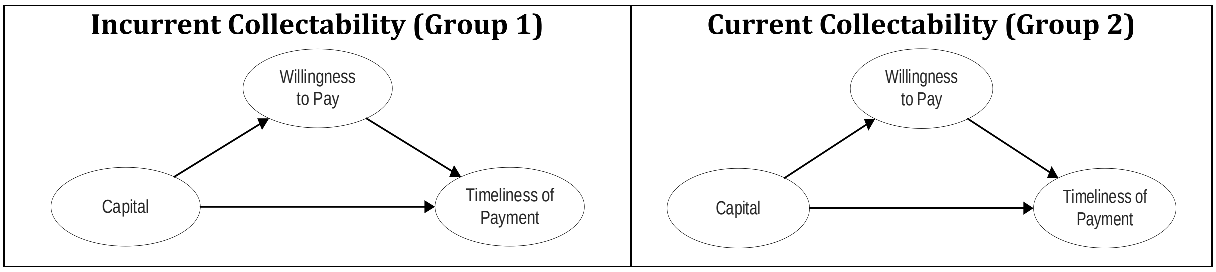

Figure 4. Research Model Multigroup Approach

The data was analyzed using SmartPLS 4.0 software. The analysis was carried out twice, namely on a model with an interaction approach and a model with a multigroup approach. Measurement models and structural models are created simultaneously to produce structural model equations. The model that has been fit is carried out further analysis to examine indirect effects, so as to expound the relationship between Capital and Timeliness of Payment of Bank mortgage debtors through Willingness to Pay as a mediation and moderated by Collectability Status. In this article, will evaluate statistical methods to compare inner models between groups, compare indirect effects between groups, and examine indirect effects on each group.

C. RESULT AND DISCUSSION

1. Measurement Model Evaluation

The measurement model is evaluated to measure the extent to which the measurements used in the SEM-PLS model represent the concept in question. Model evaluation can be done by looking at validity and reliability. Evaluation of measurement models is carried out with a multigroup and interaction approach. The results of the analysis are presented in Table 2 and Table 3.

Table 2. Reliability and validity converge with Multigroup and Interaction Approaches

Variable	Incurrent		Current		Interaction	
	CR	AVE	CR	AVE	CR	AVE
X	0.822	0.549	0.822	0.518	0.955	0.876
M	0.901	0.753	0.710	0.546	0.821	0.840
Y	0.812	0.684	0.856	0.748	0.846	0.733
Group*X					0.830	0.620

Based on Table 2, it can be seen that all CR (Composite Reliability) values ≥ 0.7, Whether in incurrent groups, current groups, or with an interaction approach. In addition, the value of AVE in both multigroup and interaction approaches is greater than 0.5. Thus, convergent reliability and validity are met, both multigroup and interactionally. For exogenous variables, the largest CR and AVE values are in the interaction approach. For the mediating variables, the largest CR values is in the multigroup approach in Group 1, while the largest AVE value is in the interaction approach. In pure endogenous variables, the largest CR and AVE values are in the multigroup approach in Group 2. Because the CR and AVE values for all variables are satisfactory. Discriminant validity relates to the principle that the gauges of different latent variables are not highly correlated. Measurement of discriminant validity using cross loading. Outer loading measures the correlation between indicators and latent variables, and is said to be valid if the Outer loading value ≥ 0.5.

Tabel 3. Higher order construct validation

Indicators	Incurrent			Current			Interaction		
	Outer Loading	T stat	p-value	Outer Loading	T stat	p-value	Outer Loading	T stat	p-value
X_1	0.865	4.714	0.000	0.740	3.054	0.000	0.746	2.875	0.000
X_2	0.850	6.928	0.000	0.804	2.192	0.000	0.860	4.040	0.000
X_3	0.888	5.871	0.000	0.741	2.825	0.000	0.751	3.237	0.000
M_1	0.749	4.202	0.000	0.759	9.990	0.000	0.595	8.283	0.000
M_2	0.752	6.416	0.000	0.748	12.175	0.000	0.740	14.100	0.000
M_3	0.760	6.540	0.000	0.792	10.794	0.000	0.709	12.443	0.000
M_4	0.722	6.544	0.000	0.797	11.318	0.000	0.712	13.286	0.000
M_5	0.833	6.999	0.000	0.767	8.329	0.000	0.701	10.905	0.000
Y_1	0.863	7.496	0.000	0.860	22.198	0.000	0.861	25.248	0.000
Y_2	0.790	5.430	0.000	0.869	26.339	0.000	0.851	29.562	0.000
Group*X_1							0.964	3.235	0.000
Group*X_2							0.898	3.153	0.000
Group*X_3							0.944	3.244	0.000

Based on Table 3, it can be seen that the strongest indicator (largest outer loading value) for exogenous variable (X) is X_2, in the multigroup and interaction approaches. In the mediation variable (M), the strongest indicator for the multigroup approach is M_5 in Group 1, and M_4 in Group 2. While in the interaction approach, the strongest indicator is M_2. For endogenous variable (Y), the strongest indicator is Y_1 in the multigroup approach in Group 1, and Y_2 in Group 2. Y_1 is also the strongest indicator in the interaction approach. All outer loadings are more than 0.5 and significant, which indicates that discriminant validity has been met. Based on Table 2 and Table 3, it can be concluded that the evaluation of the measurement model can be fulfilled according to the specified criteria, so the analysis can continue.

2. Structural Model

Structural model testing (inner model) aims to test hypotheses in research. Hypothesis testing is carried out on indirect effect and moderation, both on multigroup approaches and interaction approaches. The results of modeling using SEM-PLS are presented in Figure 4 and Figure 5.

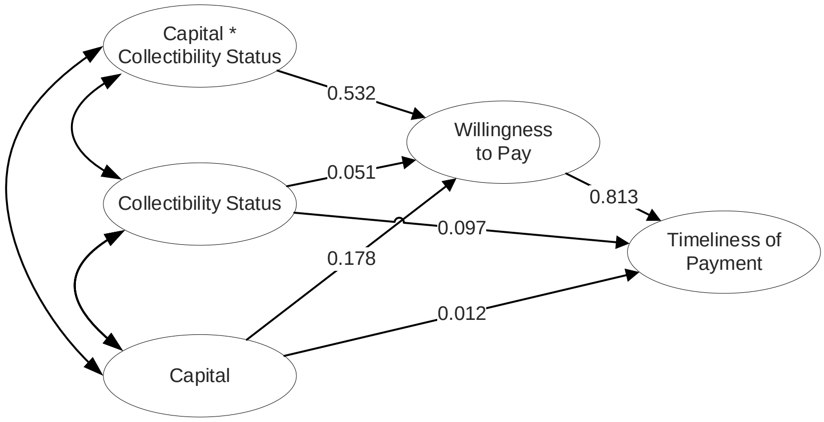

Figure 5. Estimate Inner Model Interaction Approach

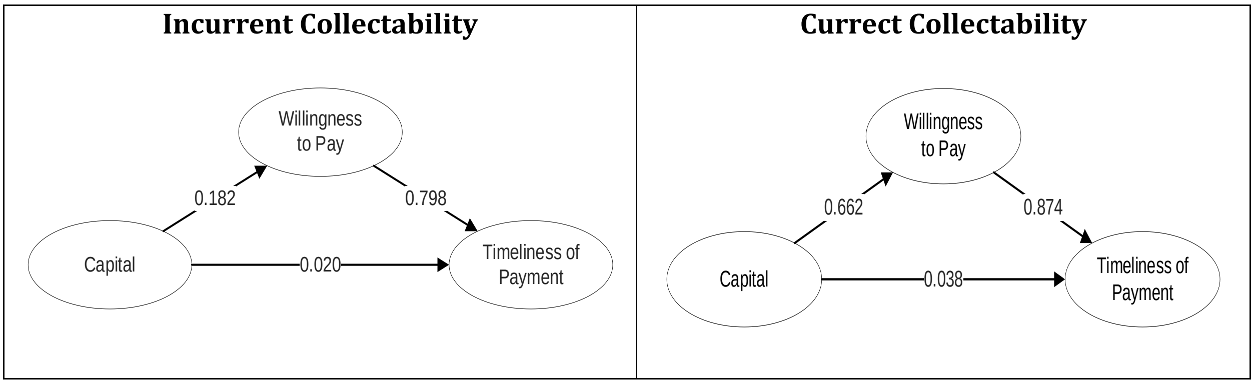

Figure 6. Estimate Inner Model Multigroup Approach

Based on Figure 5, the groups are coded 0 = Incurrent and 1 = Current. The estimated indirect effect with the interaction approach is as large as $0.178 \times 0.813 = 0.145$ for Incurrent Collectability and $(0.178 + 0.532) \times 0.813 = 0.577$ for Current Collectability. Based on Figure 6, the estimated indirect effect is as large as $0.182 \times 0.798 = 0.145$ for Collectability Incurrent and $0.662 \times 0.874 = 0.578$ for Current Collectability. The interaction and multigroup approach give results that Capital has a positive effect on Timeliness of Payment, both directly and indirectly. Willingness to Pay has a direct positive effect on Timeliness of Payment. Furthermore, indirect effect testing (mediation) moderated by collectability status variables was carried out. Table 4 presents the results of indirect effect testing with moderation of both interaction and multigroup approaches.

Table 4. Moderate Indirect Effect Testing

	Interaction Approach	**Multigroup Approach**
Estimator Difference	0.432	0.433
Interval Bootstrap (95%)	(0.158 ; 0.678) Bias 0.282	(0.218 ; 0.592) Bias 0.185
p-value Difference Test	0.039	0.010

Based on Table 4, it can be seen that the results of indirect effect testing on moderation with interaction and multigroup approaches are not much different, both in terms of estimator differences, bootstrap intervals, and different test opportunity values. The difference seems to be slight, in the multigroup approach the bootstrap interval bias is smaller than in the interaction approach. However, both provide equally significant results on the indirect effect of Capital's relationship on the Timeliness of Payment through Willingness to Pay moderated by Collectibility Status. The result of this research agree with research conducted by Ryu (2015), Ryu & Cheong (2017), Igartua & Hayes (2021). When viewed from the magnitude of the effect, it is known that the effect of Current Collectability Status is greater than the effect of Incurrect Collectability Status, either directly or indirectly. Thus, it can be said that the moderation of the Current Collectability Status reinforces Capital's indirect effect on the Timeliness of Payment through the Willingness to Pay of Bank X mortgage debtors.

3. Goodness of Fit

Q^2 has a value range $0 < Q^2 < 1$, where the closer to 1, the better the model. The results of the calculation of Q^2 values are presented in the Table 5.

Table 5. Goodness of Fit Model

Variable	**Incurrent**		**Current**		**Interaction Approach**	
	$\boldsymbol{R^2}$	$\boldsymbol{Q^2}$	$\boldsymbol{R^2}$	$\boldsymbol{Q^2}$	$\boldsymbol{R^2}$	$\boldsymbol{Q^2}$
Willingness to Pay	0.330	0.842	0.438	0.893	0.124	0.704
Timeliness of Payment	0.764		0.810		0.662	

Based on Table 5, it can be seen the value of Q-Square Predictive Relevance to measure the goodness of the model. Q^2 in the incurrect collectability group of 0.842 provides information that 84.2% of the data on the timeliness of paying bank mortgages on incurrect collectability status is explained by the model, while the remaining 15.8% is explained by other variables outside the model. Q^2 in the current collectability group of 0.893 provides information that 89.3% of the data on the timeliness of paying bank mortgages on the current collectability status is explained by the model, while the remaining 10.7% is explained by other variables outside the model. On the interaction approach, Q^2 0.704 provides information that 70.4% of the data on the timeliness of paying bank mortgages is explained by the model, while the remaining 29.6% is explained by other variables outside the model. The Q-square Predictive Relevance value in both methods is quite high, indicating that the model is good. There is little difference that Q^2 modeling with a multigroup approach is higher than in the interaction approach.

D. CONCLUSION AND SUGGESTIONS

The results of the analysis concluded that Collectability Status moderates the indirect relationship between Capital and the Timeliness of Payment through Willingness to Pay in Bank X mortgage debtors. Based on interaction and multigroup approaches, both methods provide the same analysis results, namely Current Collectability Status strengthens the relationship. Debtors with current collectability status more strongly effect the Timeliness of Payment than debtors with incurrect collectability status. Based on the method approach that has been done, results are obtained that are not much different between the two methods. Both gave the same result, namely indirect effect with significant moderation in this case. However, the researchers recommend a multigroup approach to data that has categorical moderation variables because differences between groups can be directly observed without adding interaction variables in the model. Based on the test results, the bias in the multigroup approach is smaller than in the interaction approach. While the Q^2 multigroup approach is larger than the interaction approach. This research is limited to the case of Bank X mortgages. In the next research can be developed by conducting simulation studies to provide more general results.

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