

STRUCTURAL EQUATION MODELING MULTIGROUP INDIRECT EFFECTS ON BANK MORTGAGE PAYMENT TIMELINESS

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ABSTRACT

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Structural Equation Modeling (SEM) is a multivariate statistical method that is used to thoroughly explain the relationship between latent variables simultaneously. Until now, SEM continues to grow in research. This research was conducted to examine the indirect effect on the timeliness of paying bank mortgages with a multi-group moderation approach. Analysis to identify factors that influence the timeliness of paying bank mortgages is an important step for banks before extending credit to prospective customers. The data used in this research is secondary data from research grants from National Competitive Basic Research. The data scale used is the Likert scale for exogenous, mediating endogenous, and pure endogenous variables. While the moderating variable uses a dummy variable. The results of the study show that the indirect effect of Capacity and Capital on Pay on Time for Bank Mortgage customers has a significant effect, both on non-current collectibility status and current collectibility status. This is evidenced by the Sobel test value greater than $Z_{0.025}(1.96)$ on the indirect effect test, and the p -value of the Wald test is smaller than $\alpha(0.05)$ on the moderation indirect effect test. Mediator variable is able to increase the effect of exogenous variables on endogenous variable Customers with current collectibility status have a stronger influence on timely payments than customers with non-current collectibility status.



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1. INTRODUCTION

Structural Equation Modeling (SEM) is a development of path analysis, which is path analysis was first developed by Wright (1934) as a means of studying the direct and indirect effects of several variables, in which some variables are seen as causes, and other variables are seen as effects [1]. Structural modeling simultaneously measures the relationship between variables and the relationship between variables and their indicators, so it is considered a complex method [2]. Basically, structural modeling is the development of multiple regression analysis and path analysis, both of which are forms of multivariate analysis models. Regression analysis only involves predictor and response variables. While in the path analysis there are exogenous, endogenous mediating, and pure endogenous variables [3]. Therefore, in the path analysis there are direct and indirect effects. In addition, there are times when the relationship between exogenous and endogenous variables is strengthened or weakened by moderating variables. However, the most important feature is that the moderating variable is not influenced by exogenous variables. Introducing a moderator within model increases the model's complexity and enhances the predictive power of study [4].

In field conditions, many samples come from two populations or two groups. These conditions can be overcome using modeling with a multigroup approach. In principle, the analysis of moderating variables with the multigroup method is to perform structural modeling on two or more groups. For example, in the collectability group, current and non-current bank mortgage payments. Bank is a business entity that collects funds from the public in the form of savings and distributes them in the form of loans or credit. One form of credit distribution facilitated by the Bank is the Housing Loan. From the consumer side, mortgage facilities are still the top choice in buying residential property with a share of 74.83% of total financing [5]. Banks must be more careful in providing loans to prospective customers so as not to suffer losses.

Analysis to identify factors that influence the timeliness of paying bank mortgages is an important step for banks before extending credit to prospective customers. By conducting this analysis, the Bank can take steps to minimize the risk of losses that may arise due to bad credit or default. This method allows the Bank to maintain the health of its credit portfolio, optimize lending, and increase efficiency in overall credit risk management.

The development of the indirect effect of multigroup moderation has not been carried out by many researchers. Research by [6] 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. Another research was conducted by [7] resulted in the finding that institutional ownership moderates the indirect effect of sustainability on company performance through variable leverage. This previous research used an interaction approach for moderation analysis, not multigroup.

Multigroup analysis (MGA) is an approach that has been broadly used for group comparisons. It is a set of advanced techniques that are usually applied when researchers want to examine differences between categorical variables [8]. In some cases, moderation and mediation are analyzed separately and the results of these analyzes are interpreted together to describe the combined effect of moderation and mediation [9]. Previous research conducted by [10] aims to determine the relationship between company resources and hotel performance, environmental orientation, and innovation. This study only discusses the indirect effect on SEM, but does not discuss the indirect effect of multigroup moderation on SEM [10].

Based on the phenomena that have been described, this study will carry out structural modeling, namely identifying the indirect effect of multigroup moderation in the case of timely payment of bank mortgages. The urgency of this research was to carry out theoretical development of the indirect effects and total effects moderating of multigroups. Where in the field conditions many samples were found to come from two groups. Classification of KPR debtor installment payment status will be the focus of this research. This classification is referred to as collectibility status which is divided into current and bad. In this research, collectibility status will be a moderating variable.

2. RESEARCH METHODS

2.1 Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is a multivariate analysis technique that combines aspects of factor analysis and multiple regression which allows researchers to simultaneously examine a series of dependency relationships between indicators and latent variables as well as between several latent variables [11]. SEM is an integrated analysis between confirmatory factor analysis, principal component analysis and regression analysis, path analysis, or a system of simultaneous equations [3]. In SEM there are two component models, namely the measurement model and the structural model. the measurement model explains the relationship between indicators variable and variables [12]. The structural model defines the relationship between latent variables [13]. The analysis commonly used in structural models is path analysis. The complete model (hybrid), in Structural Equation Modeling is presented in Equation (1) [14].

$$\eta = B\eta^* + \Gamma\xi + \zeta \quad (1)$$

Where:

- η : pure endogenous latent variable
- η^* : mediating endogenous latent variable
- B : coefficient of mediating endogenous latent variable
- Γ : coefficient of exogenous latent variable
- ξ : exogenous latent variable
- ζ : model error

2.2 Assumptions

Two critically important assumptions associated with Structural Equation Modeling (SEM), in the analysis of covariance and mean structures, is the requirement that the data are of a continuous scale and have a multivariate normal distribution [13]. These underlying assumptions are linked to large-sample theory within which SEM is embedded. Other source say that several assumptions in Structural Equation Modeling [15] is between variables have a linear relationship. In checking linearity, the Regression Specification Error Test (RESET) can be used.

2.3 Moderating Variable

Moderating variables are variables that strengthen or weaken the influence of exogenous (predictor or independent) variables on endogenous (responsive or dependent) variables [2]. One of the important features is that the moderating variable is not influenced by exogenous (explanatory) variables. In general, the effect of the moderating variable is indicated by the product of the exogenous variable indicator and the moderating variable indicator.

2.4 Indirect Effects Test

Mediation occurs when the relationship between exogenous variables and endogenous variables is transmitted through mediating variables [16]. According to [16], within the framework of path analysis, mediated influence is referred to as indirect influence. In general, the indirect effect can be expressed as the product of two or more path coefficients, depending on the number of intermediary variables between exogenous variables and pure endogenous variables [17]. The indirect effect test method can use the Sobel test in the form of the z statistic with the formula presented in Equation (2).

$$z = \frac{(p_1 \times p_2)}{\sqrt{p_1^2 \times SE_{p_1}^2 + p_2^2 \times SE_{p_2}^2}} \quad (2)$$

Where:

- p_1 : path coefficient of the effect of exogenous variables on mediating variables
- p_2 : path coefficient of the effect of mediating variables on pure endogenous variables
- SE_{p_1} : standard error for the coefficients p_1
- SE_{p_2} : standard error for the coefficients p_2

2.5 Moderation Indirect Effect Test

A multi-group analysis was applied and the model was compared to find out whether there is a significant difference between unconstrained and constrained models [18]. Testing the indirect moderating effect can be done using a subgroup approach, the sample is separated into subgroups based on moderator variables, and the indirect effect is estimated in each group and compared between groups [16]. The type of data used in the moderator variable is categorical. Hypothesis can be written:

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

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

In testing the limits of the equation, $a_{(G_1)}b_{(G_1)} - a_{(G_2)}b_{(G_2)} = 0$ you can use the Wald test [19]. The Wald test statistic determines the extent to which the parameter estimates in the model differ by zero with the sampling error taken into account. Wald's stats are obtained by:

$$W = \frac{\hat{\theta}_1^2}{avar(\hat{\theta}_1)} \quad (3)$$

Where $avar(\hat{\theta}_1)$ is the asymptotic variance estimate of $\hat{\theta}_1$, with degrees of freedom = 1. Equation (3) is the square of the usual Z ratio to test the significance of parameter estimates. Thus, the W can be seen as a generalization of the ordinary Z test. In testing the indirect effect between group 1 (G_1) and group 2 (G_2), $\hat{\theta}_1 = \hat{a}_{(G_1)}\hat{b}_{(G_1)} - \hat{a}_{(G_2)}\hat{b}_{(G_2)}$ and $avar(\hat{\theta}_1)$ asymptotic variance estimation $[\hat{a}_{(G_1)}\hat{b}_{(G_1)} - \hat{a}_{(G_2)}\hat{b}_{(G_2)}]$.

2.6 Research Data

The data used in this research is in the form of latent variable data from questionnaires given to mortgage debtor customers. The data was obtained from research conducted by Fernandes in 2022 with 4 national banks in Indonesia. Each bank took a sample of 500 respondents, which means there are 2000 respondents. Taking 500 data samples from each bank aims to ensure that the samples used fulfill the central limit theorem, where the larger the sample size, the closer it is to a normal distribution. The large sample size complies with the central limit theorem, so it is assumed that the data are close to normal distribution. This data was obtained through distributing questionnaires to debtors.

The variables used in this study consisted of exogenous variables, mediating endogenous variables, pure endogenous variables, and moderating variables in the form of dummy variables. The scale used in this study is the Likert scale. A complete explanation of the variables is presented in Table 1.

Table 1. Research Variables

Variable	Indicators
Capacity (X_1)	Customer income
	Ability to pay installments
	Ability to complete credit on time
Capital (X_2)	Fixed source of income
	Having other business fields as a source of income
	Have savings or deposits in the bank
Willingness to Pay (Y_1)	Consultation
	Documents presented
	Methods and places of payment of credit
Pay on time (Y_2)	Payment deadline
	Desire is always on time to pay
Collectability status (M)	Always on time payment per month
	0: non-current 1: current

2.7 Research Methods

This study uses *Structural Equation Modeling* with a multi-group approach. Before the analysis is carried out, the assumptions underlying the SEM are first examined, such as the assumption of linearity. The number of the sample size is in line with the normal distribution. The central limit theorem states that the sample will approach a normal distribution if the sample size is large. Because the sample used in this

study was 2,000, the data distribution is close to a multivariate normal distribution, so there is no need to check the normality assumption.

The measurement model and the structural model are made simultaneously to produce structural model equations. The fit model is further analyzed to test the indirect effect, so that it can explain the relationship between Capacity and Capital on the Timeliness of Paying for Bank Mortgage customers through Willingness to Pay mediation and moderated by Collectability Status. The software used in this research is AMOS. The research model is presented in **Figure 1**.

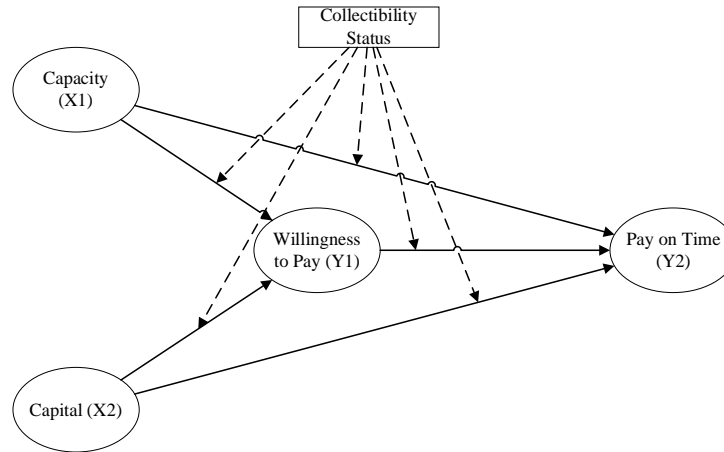


Figure 1. Research Model

The explicit analysis steps are as follows.

1. Assign variables and indicators to exogenous, mediating, and endogenous variables.
2. Design measurement and structural model.
3. Check linearity assumptions.
4. Carry out simultaneous modeling of the measurement model and structural model to see the relationship between latent variables. Structural modeling is carried out in multigroup approach.
5. Conduct indirect effect testing. Then do a moderation test to indirect effect (mediating effect).
6. Interpret and draw conclusions.

3. RESULTS AND DISCUSSION

3.1 Linearity Assumption Check

The assumption that must be met in Structural Equation Modeling is linearity. Testing the assumption of linearity is carried out using the Regression Specification Error Test (RESET). The results of the model linearity test are presented in **Table 2**.

Table 2. Linearity Test Results

Variable	p-values	Connection
X_1 with Y_1	0.8779	linear
X_1 with Y_2	0.9556	linear
X_2 with Y_1	0.4937	linear
X_2 with Y_2	0.9453	linear
Y_1 with Y_2	0.4875	linear

Based on **Table 2**, it can be seen that all relationships between exogenous variables and endogenous variables have a p-value > 0.05 (α). Therefore, all relationships between variables are linear, so that the assumption of linearity is met.

3.2 Measurement Model

In the measurement model, the indicator with the largest loading factor value indicates that the indikator is the strongest or most dominant measure in measuring the latent variable. The result of the loading factors for each variable are presented in **Table 3**.

Table 3. Measurement Model

Capacity (X_1)	λ_{1i}	Capital (X_2)	λ_{2i}	Willingness to Pay (Y_1)	λ_{3i}	Pay on Time (Y_2)	λ_{4i}
$X_{1.1}$	0.588	$X_{2.1}$	0.734	$Y_{1.1}$	0.543	$Y_{2.1}$	0.692
$X_{1.2}$	0.608	$X_{2.2}$	0.808	$Y_{1.2}$	0.585	$Y_{2.2}$	0.685
$X_{1.3}$	0.633	$X_{2.3}$	0.560	$Y_{1.3}$	0.570		
				$Y_{1.4}$	0.586		
				$Y_{1.5}$	0.592		

Based on **Table 3**, it can be seen that the strongest indicator in Capacity variables is $X_{1.3}$ which is equal to 0.633, the strongest indicator in Capital variables is $X_{2.2}$ which is equal to 0.808. The strongest indicator in Willingness to Pay variable is $Y_{1.5}$ which is equal to 0.592, then the strongest indicator in Pay on Time variable is $Y_{2.1}$ which is equal to 0.692.

3.3 Structural Equation Modeling

At this stage, structural model analysis is carried out to determine the relationship between latent variables. The results of a fit model are presented in **Figure 2**. G1 is the path coefficient value in group 1 with Collectability Status = 0 (Not Current). While G2 is the value of the path coefficient in group 2 with Collectability Status = 1 (Current).

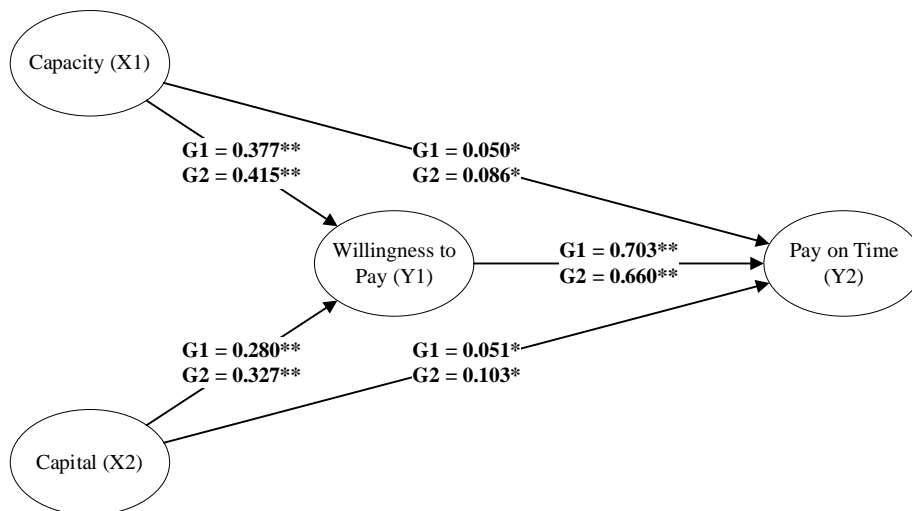


Figure 1. Structural Equation Modeling

3.4 Indirect Effect Testing

Table 3 shows the estimation of testing the indirect effect of Capacity and Capital on Pay on Time through Willingness to Pay on Collectibility that is not smooth and smooth. Testing for each indirect effect is carried out using the Sobel Test.

Table 4. Indirect Effect Testing

Exogenous Variables	Estimates			Sobel	$Z_{0.025}$
	\hat{p}_1	\hat{p}_2	$\hat{p}_1\hat{p}_2$		
Group 1 (non-current collectibility)					
Capacity	0.377	0.703	0.265	13.843	1.96
Capital	0.280	0.703	0.197	10.776	1.96
Group 2 (current collectibility)					
Capacity	0.415	0.660	0.274	6.682	1.96
Capital	0.327	0.660	0.216	5.592	1.96

Based on **Table 4**, it can be seen that the statistical value of the Sobel test is greater than $Z_{0.025}$ (1.96). Thus, it can be said that Willingness to Pay is significant in mediating the relationship between Capacity and Capital to Pay on Time for Bank Mortgage customers, both on current and non-current collectibility. Mediating variable is able to significantly increase the influence of exogenous variables on endogenous variable.

3.5 Testing the Indirect Effect of Moderation

The indirect effect between group 1 and group 2 was compared with the Wald test. The test results are presented in **Table 5**.

Table 5. Testing the Indirect Effect of Moderation

Exogenous Variables	Difference	Wald	p-values
Capacity	-0.009	3.972	0.046
Capital	-0.019	8.593	0.003

Based on **Table 5**, it can be seen that all p-values are less than α (0.05). Thus, it can be said that the Willingness to Pay in an indirect effect shows the difference in Collectibility Status (not current and smooth) of the customer's Capacity and Capital on the timeliness of mortgage payments at the Bank. Capacity and Capital for customers with current Collectibility are stronger on the timeliness of Bank mortgage payments.

4. CONCLUSION

This article examines the indirect effect of multigroup moderation on Structural Equation Modeling with the Wald difference test approach. Testing for group differences in indirect effects is a special case of testing moderated indirect effects where the moderator is a categorical variable. The conclusion that can be drawn in this study is that the indirect effect of Capacity and Capital on Pay on Time on Bank Mortgage customers has a significant effect, both on non-current collectibility status and current collectibility status. The variable that plays a mediating variable, namely Willingness to Pay (Y_1) is able to increase the effect of exogenous variables on endogenous variable. Customers with current collectibility status have a stronger influence on timely payments than customers with non-current collectibility status.

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REFERENCES

- [1] S. Wright, "The Method of Path Coefficient," *The Annals of Mathematical*, vol. 5, no. 3, pp. 161-215, 1934.
- [2] Solimun, A. A. R. Fernandes and Nurjannah, *Metode Statistika Multivariat Pemodelan Persamaan Struktural (SEM)*, Malang: UB Press, 2017.
- [3] Solimun, Nurjannah, L. Amaliana and A. A. R. Fernandes, *Metode Statistika Multivariat Generalized Structured Component Analysis (GSCA) Pemodelan Persamaan Struktural (SEM)*, Malang: UB Press, 2019.
- [4] A. H. Ngah, S. Gabarre, b. Eneizan and N. Asri, "Mediated and Moderated Model of The Willingness to Pay for Halal Transportation," *Journal of Islamic Marketing*, pp. 1-21, 2020.
- [5] D. Komunikasi, "Bank Indonesia," SHPR TRIWULAN I 2023: PERKEMBANGAN HARGA PROPERTI RESIDENSIAL MENINGKAT TERBATAS, 17 Mei 2023. [Online]. Available: https://www.bi.go.id/id/publikasi/ruang-media/news-release/Pages/sp_2513023.aspx.
- [6] R. F. Levant, M. C. Parent, E. R. McCurdy and T. C. Bradstreet, "Moderated Mediation of The Relationship Between Masculinity Ideology Outcome Expectations, and Energy Drink Use," *Health Psychology*, vol. 34, no. 11, pp. 1100-1106, 2015.
- [7] T. A. Tristanto, Nugraha, I. Waspada, Mayasari and P. Kurniati, "Sustainability Performance Impact of Corporate Performance in Indonesia Banking," *Journal of Eastern European and Central Asian Research*, vol. 10, no. 4, pp. 668-678, 2023.
- [8] J.-H. Cheah, S. Amaro and J. L. Roldán, "Multigroup Analysis of More Than Two Groups in PLS-SEM: A Review,

- Illustration, and Recommendations,” *Journal of Business Research*, vol. 156, 2023.
- [9] J. R. Edwards and L. S. Lambert, “Methods for Integrating Moderation and Mediation: A General Analytical Framework Using Moderated Path Analysis,” *Psychological Method*, vol. 12, no. 1, pp. 1-22, 2007.
- [10] M. Aboelmaged, “Direct and Indirect Effects of Eco-Innovation, Environmental Orientation and Supplier Collaboration on Hotel Performance: An Empirical Study,” *Journal of Cleaner Production*, vol. 184, pp. 537-549, 2018.
- [11] J. F. Hair, W. C. Black, B. J. Babin and R. E. Anderson, *Multivariate Data Analysis A Global Perspective*, 7th ed., Boston: Pearson, 2010.
- [12] Z. Hikmah, H. Wijayanti and M. N. Aidi, “Selection of The Best SEM Model to Identify Factors Affecting Marketing Performance in The ICT Industry,” *BAREKENG: Journal of Mathematics and Its Applications*, vol. 17, no. 2, pp. 1149 - 1162, 2023.
- [13] B. M. Byrne, *Structural Equation Modeling with AMOS*, London: Routledge, 2010.
- [14] R. Johnson and D. Wichern, *Applied Multivariate Statistical Analysis*, 6th ed., London: Pearson, 2014.
- [15] S. Haryono and P. Wardoyo, *Structural Equation Modeling untuk Penelitian Manajemen Menggunakan AMOS 18.00*, Jawa Barat: Badan Penerbit PT. Intermedia Personalia Utama, 2012.
- [16] E. Ryu, “Multiple-group Analysis Approach to Testing Group Difference in Indirect Effects,” *Behavior Research Methods*, vol. 47, pp. 484-493, 2015.
- [17] W. Chan, “Comparing Indirect Effects in SEM: A Sequential Model Fitting Method Using Covariance-Equivalent Specifications,” *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 14, no. 2, pp. 326-346, 2007.
- [18] A. A. Esubalew and A. Raghurama, “Commercial Bank Financing to Micro, Small, and Medium Enterprises (MSMEs): The Mediating and Multigroup Effect Analysis,” *Journal of Small Business & Entrepreneurship*, pp. 1-29, 2020.
- [19] K. A. Bollen, *Structural Equations with Latent Variables*, New York: Wiley, 1989.