

Article

Health Belief Model of Jambi City Community Against Covid-19 Vaccination with Structural Equation Modeling (SEM) Method

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Abstract. The community's HBM (Health Belief Model) analysis of the COVID-19 vaccination needs to be done. This perceived threat assessment is based on perceived vulnerability and seriousness. Judgments to behave in response to perceived threats are also influenced by cues to action. Variables that cannot be explained directly or variables that require explanation from other variables are called latent variables. Latent variables consist of exogenous and endogenous variables. This study aims to analyze the public health belief model of the city of Jambi towards COVID-19 vaccination with the structural equation modeling (SEM) method. The results showed that the health belief model for COVID-19 vaccination in Jambi City, vaccination actions were significantly influenced by perceptions of benefits and barriers. Perceived benefits and barriers were significantly affected by perceived severity and seriousness and then perceived severity and seriousness were significantly influenced by cues to action. However, demographics including age, occupation, income and beliefs in this study did not significantly influence a person to vaccinate. The proposed model can be accepted based on the goodness of fit indicator.

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1. Introduction

Jambi Province is a province located in western Indonesia that is also affected by COVID-19. Based on data from the COVID-19 Task Force of Jambi Province, until March 2021 the number of people who were confirmed positive reached 5611 people (<http://corona.jambiprov.go.id>). The prolonged COVID-19 outbreak has had a significant impact on Indonesia's health sector and economy. The President of the Republic of Indonesia (RI) has established a national team to accelerate the development of the COVID-19 vaccine. Presidential Decree No. 18/2020 issued on September 3, 2020 stipulates the establishment of a COVID-19 vaccine development team under the supervision of the Coordinating Minister for Economic Affairs.

On October 6, 2020, the President signed and issued a Presidential Regulation on vaccine procurement and implementation of vaccination programs to combat the COVID-19 pandemic. The regulation stipulates that the government will prepare the procurement and distribution of vaccines and the implementation of vaccinations. The president stipulates PT. Bio farma, a state-owned pharmaceutical company, to provide vaccines through cooperation with various international institutions. This regulation also stipulates that the Ministry of Health regulates the distribution of vaccines and national vaccination programs. The hope that the vaccine can prevent COVID-19 in the medical world, is not coupled with the trust of the world community. According to kompas daily news (2021) The latest global vaccine trust study says that political polarization and misinformation from cyberspace threatens vaccination programs around the world including Indonesia. In the world of health, a person's belief to take preventive measures against disease is called the Health Belief Model (HBM).

The Health Belief Model is a cognitive model, which means that cognitive processes are influenced by information from their environment [1,2,3,4,5,6,7,8]. The possibility of individuals will take certain disease prevention measures depending on the results of health assessments (health belief) namely threats and considerations about benefits and losses (benefit and cost). This perceived threat assessment is based on perceived vulnerability and seriousness. Judgments to behave against perceived threats are also influenced by cues to action. Threats, seriousness, immunity as well as considerations about gains and disadvantages are influenced by demographic variables such as age and beliefs and sociopsychological variables such as social status.

Variables that cannot be explained directly or variables that require an explanation of other variables are called latent variables. While variables that can explain latent variables are called indicator variables. According to [9], the analysis that discusses the relationship between variables in which there contain latent variables and indicator variables is called SEM (Structural Equation Modeling). Structural Equation Modeling (SEM) is a multivariable analysis technique that can be used to describe the simultaneous interrelationship of linear relationships of observational variables that simultaneously involve latent variables that cannot be measured directly [10,11,12,13]. In general, SEM assumes that the observational variable is a continuous variable that distributes a normal multivariate distribution [9]. Thus this study analyzed the public Health Belief Model against COVID-19 vaccination, especially in Jambi City using SEM (Structural Equation Modeling) analysis.

2. Experimental Section

The data used in this study is primary data obtained by researchers by distributing questionnaires. The sample of this research is a candidate for vaccine receptor in Jambi City. The samples used in this study were respondents who were taken from vaccine receptor candidates scattered in the city of Jambi in each sub-district. The research sample area is Jambi City. The variables used in this study are shown in the following Table 1.

Table 1. Research Variable

Latent Variable	Manifest Variable	Definition
Demographics (X_1)	Age (X_{11})	Age of vaccine receptor candidate
	Last Education (X_{12})	The education of the vaccine receptor candidate
	Work (X_{13})	Activities carried out by prospective receptors to meet their life needs
	Religion (X_{14})	Beliefs held by vaccine receptor candidate
	Income (X_{15})	Monthly generation of vaccine receptor candidates
Cues to action(X_2)	Vaccination Education(X_{21})	Counseling given to vaccine receptor candidates
	Information Media (X_{22})	Media used to disseminate vaccines
	Intervention(X_{23})	There is government intervention as well as community leaders and health institutions
Perceived Severity/Seriousness (Y_1)	Severity(Y_{11})	Action of receptor candidate to prevent disease by vaccination due to susceptibility to disease
	Seriousnes (Y_{12})	The action of the receptor candidate to seek treatment because of the seriousness of the disease in the community
	Threat Knowledge(Y_{13})	Knowledge of potential receptor to dangerCovid-19
	Confidence(Y_{14})	Vaccine receptor candidate confidence in harm Covid-19
Perceived benefits and Perceived barriers (Y_2)	Efektiveness(Y_{21})	The vaccine has been clinically tested in accordance with health standards

Vaccination Measures (Z_1)	Halal (Y_{22})	The vaccine has obtained a halal certificate from MUI
	Safety (Y_{23})	There are no side effects after vaccination
	Vaccination Access (Y_{24})	Vaccination service place
	Understanding Vaccination (Z_{11})	Understanding of prospective respondents on Covid-19 vaccination
	Willingness (Z_{12})	Willingness of prospective respondents to take part in the Covid-19 vaccination

In this study, the estimation method used is Maximum Likelihood (ML) [14,15,16,17,18,19,20,21]. According to [22], ML is effective on the number of samples between 150-400 data. To check the normality of all data variables with univariate normality and multivariate normality. A distribution is said to be normal if the data is not skewed to the left or to the right. However, it is difficult to obtain because the distribution of data will vary on skewness and negative and positive kurtosis. So according to [22] a distribution is said to be normal if the cr skewness and cr kurtosis numbers are between -2.58 and +2.58 make specifications of the model, assess model identification, estimating the model with maximum likelihood (ML). The Absolute Fit Indices test directly compares the covariance matrix of the sample and the estimate. The Absolute Fit Indices test directly compares the covariance matrix of the sample and the estimate. According to [22] goodness of fit test on absolute fit indices are GFI, RMSEA, ECVI, TLI, NFI, AGFI, RFI, IFI, CFI, PGFI and AIC.

3. Results and Discussion

Data collection was obtained directly from questionnaires distributed to the people of Jambi City by taking random samples. Respondents were 201 people spread over 11 sub-districts in Jambi City. It is hoped that the data obtained can describe the overall Health Belief Model of the Jambi City community towards Covid-19 vaccination. Before the questionnaire was used, an analysis was carried out first to determine test the quality and feasibility of the questionnaire. Analysis used is the Validity Test and Reliability Test conducted on 30 data samples. The causality relationship path diagram model of Health Belief Model (HBM) against COVID-19 vaccination are shown in the following Figure 1.

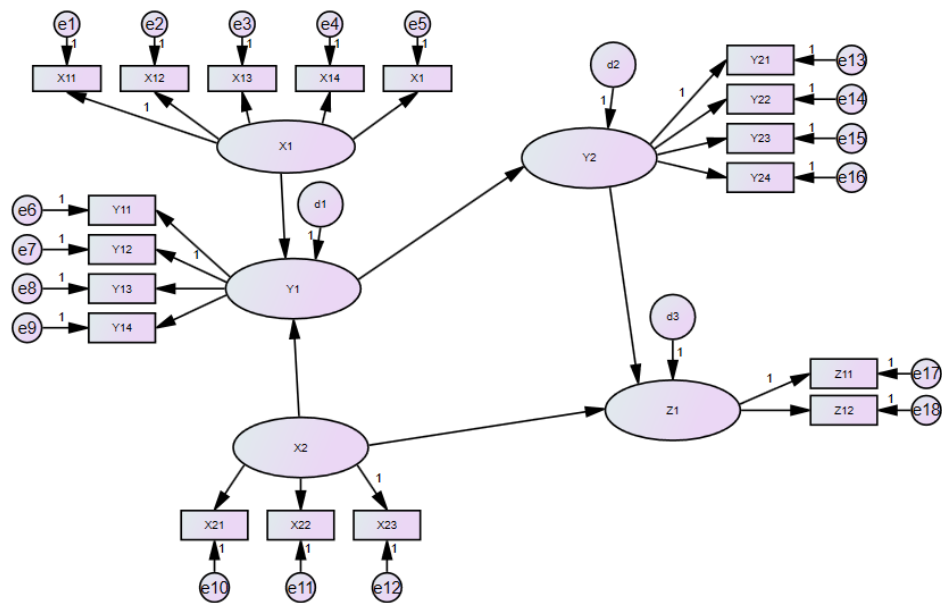


Figure 1. The Causality Relationship Path Diagram Model

The model specification is carried out by converting the path diagram into a series of structural model equations and measurement model equations. The above model is formed based on the theory of health belief model which shows the relationship between demographics, cues to action, Perceived Severity/Seriousness, and Perceived benefits and Perceived barriers to Vaccination Measures. The next stage of data analysis is through the measurement model, which is presented in Table 2.

Table 2. Loading Factor Measurement Fit Test

Variable		Factor Loading (Significance*)
Understanding Vaccination	← Vaccination Measures	0,661 (*)
Willingness	← Vaccination Measures	0,793 (*)
Intervention	← Cues to Action	0,625 (0,068)
Information Media	← Cues to Action	0,162 (*)
Education	← Cues to Action	0,529 (*)
Efektivenes	← Perceived benefits and barriers	0,810 (*)
Halal	← Perceived benefits and barriers	0,790 (*)
Safety	← Perceived benefits and barriers	0,817 (*)
Vaccination Access	← Perceived benefits and barriers	0,626 (*)
Severity	← Perceived Severity/Seriousness	0,539 (*)
Seriousnes	← Perceived Severity/Seriousness	0,561 (*)

Threat Knowledge	← Perceived Severity/Seriousness	0,733 (*)
Age	← Demographics	0,015 (*)
Last Education	← Demographics	0,615 (0,271)
Work	← Demographics	0,623 (0,268)
Religion	← Demographics	0,376 (0,283)
Income	← Demographics	0,663 (0,266)
Confidence	← Perceived Severity/Seriousness	0,762 (*)

Note. *: Significant at level 0.05

In Table 2 it can be seen that the indicator variable for the latent variable Demographics is significant only age and other variables are not significant. The information media indicator variable significantly affects the Cues Action latent variable but the loading factor value is less than 0.5. The next step is structural Model Fit Test shown in the following Table 3.

Table 3. Model Structural

Variable	Loading Factor (Significance*)
Perceived Severity/Seriousness ← Demographics	0,419 (0,22)
Perceived benefits and barriers ← Perceived Severity/Seriousness	0,926 (*)
Vaccination Measures ← Perceived benefits and barriers	0,787 (*)
Vaccination Measures ← Cuest to Action	0,651 (*)

Note. *: Significant at level 0.05

In Table 3 it can be seen that the structural model, it can be seen that the demographic variable does not significantly affect to the Perceived Severity/Seriousness variable. So that the following model is obtained. Based on the results of the measurement model and structural model, the following modifications were made to the mode are shown in following Figure 2.

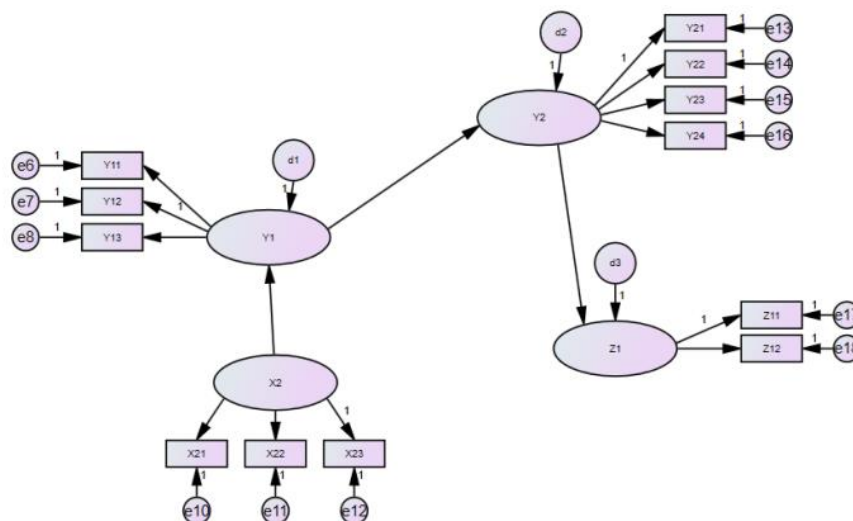


Figure 2. The Modification Model

According to Figure 2, the output of the data about loading factor measurement fit test of the modification model shown in the following Table 4.

Table 4. Loading Factor Measurement Fit Test of the Modification Model

	Variable	Factor Loading (Significance*)
Understanding Vaccination	← Vaccination Measures	0,733 (*)
Willingness	← Vaccination Measures	0,854 (*)
Intervention	← Cues to Action	0,701 (*)
Information Media	← Cues to Action	0,224 (*)
Education	← Cues to Action	0,430 (*)
Efektivenes	← Perceived benefits and barriers	0,783 (*)
Halal	← Perceived benefits and barriers	0,816 (*)
Safety	← Perceived benefits and barriers	0,796 (*)
Vaccination Access	← Perceived benefits and barriers	0,607 (*)
Severity	← Perceived Severity/Seriousness	0,598 (*)
Seriousness	← Perceived Severity/Seriousness	0,500 (*)
Threat Knowledge	← Perceived Severity/Seriousness	0,653 (*)
Perceived Benefits and barriers	← Perceived Severity/Seriousness	0,990 (*)
Perceived Severity/Seriousness	← Cues to Action	1,147(*)
Vaccination Measures	← Perceived Benefits and barriers	0,970(*)

Note. *: Significant at level 0.05

According to Table 4 can be seen that all of indicator variable are significant at level 0,05. This means that there is a significant and close relationship between independent variable and dependent variable, for example, there is a close relationship between access to vaccination and perceived benefits and barriers. When viewed from the correlation number, if it is above 0.5 it indicates a close correlation and in the other hand if it is below 0.5 it indicates that there is no close correlation. Based on table 4, the correlation between information media and cues to action as well as education and cues to action is below 0.5. However, the correlation between intervention and cues to action is above 0.5. The next step is structural Model Fit Test shown in the following Table 5.

Table 5. Model Structural of Modification Model

Variable	Loading factor (Significance*)
Perceived benefits and barriers ← Perceived Severity/Seriousness	1,55 (*)
Vaccination Measures I ← Perceived benefits and barriers	0,90 (*)
Perceived Severity and seriousness ← Cuest to Action	0,51 (*)

Note. *: Significant at level 0.05

According to Table 5 can be seen that all of indicator variable are significant at level 0,05 and the correlation number all of indicator variable above 0,5. It indicates a close correlation for all of indicator variable. In SEM, data is normally distributed univariate and multivariate. The assumption of normality can be tested with the z statistic value for skewness and the z statistic value for kurtosis. The results of the normality test can be seen in Table 6.

Table 6. Normality Test

Variable	$Z_{skewness}$	$Z_{kurtosis}$
Vaccination Education (X_{21})	-0,436	-0,874
Information Media (X_{22})	-1,382	0,680
Intervention (X_{23})	-0,293	-0,874
Severity (Y_{11})	-0,025	0,140
Seriousnes (Y_{12})	-0,228	0,146
Threat Knowledge (Y_{13})	-0,763	0,221
Efektiveness (Y_{21})	-0,208	-0,488
Halal (Y_{22})	-0,390	-0,400
Safety (Y_{23})	-0,254	-0,223
Vaccination Access(Y_{24})	-0,321	0,356
Understanding Vaccination (Z_{11})	-0,107	-0,149
Willingness (Z_{12})	-0,444	0,149
Multivariate		33,549

According to [22] a distribution is said to be normal if the numbers $Z_{skewness}$ and $Z_{kurtosis}$ are between -2.58 to +2.58. If seen in Table 2, it can be seen that all variables meet univariate and multivariate normality. It is known that the number of parameters to be estimated is 27 (k) and the number of manifest variables is 12(p).

$$\begin{aligned}
 d_f &= 1/2 [(p). (p + 1)] - k \\
 &= 1/2 [(12). (12 + 1)] - 27 \\
 &= 51
 \end{aligned}$$

So the degree of freedom is $51 > 0$ so that the model is over-identified, meaning that the model is feasible for the estimation stage.

The research model that has met the specification and model identification stages can then be estimated model. The estimation used is the Maximum Likelihood estimation. Maximum Likelihood estimation can we chosen because the sample size is 200-500 data. In the estimation stage, AMOS 2.2 software is used to help generate parameter values, because the equations are too complex to be analyzed directly manually. The overall fit test of the model in this study and the Goodness of Fit index criteria are shown in the following Table 7.

Table 7. Goodness of Fit Index Criteria

Goodness of Fit Index	Index Model	Information
GFI	0.908	Good Fit
RMSEA	0.088	Fit to the Data
ECVI	0.920	Good Fit
TLI	0.911	Good Fit
NFI	0,893	Marginal Fit
AGFI	0,859	Marginal Fit
RFI	0,861	Marginal Fit
IFI	0,932	Good Fit
CFI	0.931	Good Fit
PGFI	0,593	Close Fit
AIC	183.932	Fit to the Data

According to [22], to see a good model is a model with a CMIN on the default model being between the CMIN saturated model and the CMIN independence model. From the results of data processing using Amos software, the default CMIN model is 129.932, which is between CMIN saturated model 0.000 and CMIN independence model 1209.260. So the model is categorized as good. On a large sample and a large number of indicators, other test tools are also used. The GFI (Goodness of Fit Index) and AGFI (Adjusted Goodness of Fit Index) numbers range between 0 and 1. The closer the GFI and AGFI results are to 1, the better the model explains the data. Based on table 5, the GFI and AGFI numbers are close to 1, so the model explains the existing data better. Furthermore, NFI (Normed Fit Index), CFI (Comparative Fit Index), IFI (and RFI have a range of values between 0 and 1. Values above 0.9 indicate that the model is in good fit with the existing data. If the value is between or equal to 0.8 and 0.9, it is classified as marginal fit. RMSEA (Root Mean Square Error of Approximation) value between 0.05 and 0.08 is a good fit. However, on the result of the data RMSEA value is 0.088, it is considered that the model still fits the data. The AIC (Aikake Information Criterion) value on default model is smaller than saturated model or independence model that is indicates model fit to the data. Based on the data AIC value on default model 183, 932 is smaller than AIC value on independence model. The result based on the AIC value model fit to the data. So, based on the goodness of fit index criteria the propose model could be accepted.

4. Conclusion

The purpose of the study analyzed the public The possibility of individuals will take certain disease prevention measures depending on the results of health assessments (health belief) namely threats and considerations about benefits and losses (benefit and cost). This perceived threat assessment is based on perceived vulnerability and seriousness. Judgments to behave against perceived threats are also influenced by cues to action. Threats, seriousness, immunity as well as considerations about gains and disadvantages are influenced by demographic variables such as age and beliefs and

sociopsychological variables such as social status. Because of all factors can not be measured directly to the object, the structural equation model is implemented to construct Health Belief Model against COVID-19 vaccination especially in Jambi City. This study proved that health belief model against COVID-19 vaccination in Jambi City, vaccination measure is significantly affected by Perceived benefits and barriers. Perceived benefits and barriers is significantly affected by Perceived severity and seriousness and then by Perceived severity and seriousness is significantly affected by cues to action. However, demographics including age, occupation, income and beliefs in this study did not significantly influence someone to vaccinate. In general, the proposed model could be accepted based on t indicators of goodness of fit model GFI, RMSEA, ECVI, TLI, NFI, AGFI, RFI, IFI, CFI, PGFI and AIC.

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References

- [1] Van der Linden, S., Leiserowitz, A., & Maibach, E. (2019). The gateway belief model: A large-scale replication. *Journal of Environmental Psychology*, 62, 49-58.
- [2] Salari, R., & Filus, A. (2017). Using the health belief model to explain mothers' and fathers' intention to participate in universal parenting programs. *Prevention Science*, 18(1), 83-94.
- [3] Bae, S. Y., & Chang, P. J. (2021). The effect of coronavirus disease-19 (COVID-19) risk perception on behavioural intention towards 'untact'tourism in South Korea during the first wave of the pandemic (March 2020). *Current Issues in Tourism*, 24(7), 1017-1035.
- [4] Huang, X., Dai, S., & Xu, H. (2020). Predicting tourists' health risk preventative behaviour and travelling satisfaction in Tibet: Combining the theory of planned behaviour and health belief model. *Tourism Management Perspectives*, 33, 100589.
- [5] Gabriel, E. H., Hoch, M. C., & Cramer, R. J. (2019). Health Belief Model Scale and Theory of Planned Behavior Scale to assess attitudes and perceptions of injury prevention program participation: An exploratory factor analysis. *Journal of science and medicine in sport*, 22(5), 544-549.
- [6] Dodel, M., & Mesch, G. (2018). Cyber-victimization preventive behavior: A health belief model approach. *Computers in Human behavior*, 68, 359-367.
- [7] Livi, S., Zeri, F., & Baroni, R. (2017). Health beliefs affect the correct replacement of daily disposable contact lenses: predicting compliance with the Health Belief Model and the Theory of Planned Behaviour. *Contact Lens and Anterior Eye*, 40(1), 25-32.
- [8] Haghghi, M., Taghdisi, M. H., Nadrian, H., Moghaddam, H. R., Mahmoodi, H., & Alimohammadi, I. (2018). Safety Culture Promotion Intervention Program (SCPIP) in an oil refinery factory: an integrated application of Geller and Health Belief Models. *Safety science*, 93, 76-85.
- [9] Hair, et all. (2016). *Multivariate Data Analysis*. 7th edition. *Prentice Hall Inc., New Jersey*.

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- [10] Najaf, P., Thill, J. C., Zhang, W., & Fields, M. G. (2018). City-level urban form and traffic safety: A structural equation modeling analysis of direct and indirect effects. *Journal of transport geography*, 69, 257-270.
- [11] Pegolo, S., Yu, H., Morota, G., Bisutti, V., Rosa, G. J., Bittante, G., & Cecchinato, A. (2021). Structural equation modeling for unraveling the multivariate genomic architecture of milk proteins in dairy cattle. *Journal of Dairy Science*, 104(5), 5705-5718.
- [12] Law, L., & Fong, N. (2020). Applying partial least squares structural equation modeling (PLS-SEM) in an investigation of undergraduate students' learning transfer of academic English. *Journal of English for Academic Purposes*, 46, 100884.
- [13] Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, 173, 121092.
- [14] Allison, P. D., Williams, R., & Moral-Benito, E. (2017). Maximum likelihood for cross-lagged panel models with fixed effects. *Socius*, 3, 2378023117710578.
- [15] Farahbakhsh, M., Dekker, T. M., & Jones, P. R. ORCID: 0000-0001-7672-8397 (2019). Psychophysics with children: Evaluating the use of maximum likelihood estimators in children aged 4-15 years (QUEST plus). *Journal of Vision*, 19(6).
- [16] Maydeu-Olivares, A. (2017). Maximum likelihood estimation of structural equation models for continuous data: Standard errors and goodness of fit. *Structural Equation Modeling: A Multidisciplinary Journal*, 24(3), 383-394.
- [17] Peng, X., Li, X., Wang, C., Fu, H., & Du, Y. (2018). A maximum likelihood based nonparametric iterative adaptive method of synthetic aperture radar tomography and its application for estimating underlying topography and forest height. *Sensors*, 18(8), 2459.
- [18] Zhao, S., Shmaliy, Y. S., & Ahn, C. K. (2018). Iterative maximum likelihood FIR estimation of dynamic systems with improved robustness. *IEEE/ASME Transactions on Mechatronics*, 23(3), 1467-1476.
- [19] Nijkamp, E., Hill, M., Han, T., Zhu, S. C., & Wu, Y. N. (2020, April). On the anatomy of mcmc-based maximum likelihood learning of energy-based models. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 34, No. 04, pp. 5272-5280).
- [20] Cheng, X. (2021). Relative maximum likelihood updating of ambiguous beliefs. *Journal of Mathematical Economics*, 102587.
- [21] Ko, V., & Hjort, N. L. (2019). Copula information criterion for model selection with two-stage maximum likelihood estimation. *Econometrics and Statistics*, 12, 167-180.
- [22] Santoso, S. (2018). Structural Equation Modeling (SEM). *Gramedia*. Jakarta.