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The Comparison of WLS and DWLS Estimation Methods in SEM to Construct Health Behavior Model

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Abstract
It is unknown how reliable various point estimates, standard errors, and standard several test statistics are for standardized Structural Equation Modeling (SEM) parameters when categorical data used or misspecified models are present. This paper discusses the comparison between Weighted Least Square (WLS) and Diagonally WLS (DWLS) for examining hypothesized relations among ordinal variables. In SEM, the polychoric correlation is employed either in WLS or DWLS. This study constructs the Health behavior model as an endogenous latent variable in which exogenous latent variables are Perceived susceptibility and Health motivation. All indicators are in categorical types. Thus, data are not multivariate normal, or the model could be misspecified. This study compares the values of standard deviation and coefficient determination to determine a better model. The goodness of fit for the overall model is based on Tucker Lewis Index (TLI), Root Mean Square Error Approximation (RMSEA), and Confidence Fit Index (CFI). This present study found that the WLS estimator method tent to result in better values than DWLS's. Health motivation has a higher effect on Health behavior than Perceived susceptibility, obtained based on both estimators.

Keywords
Weighted Least Squares, Health Behavior, Diagonally Weighted Least Squares, Structural Equation Modeling

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1. INTRODUCTION

SEM is a powerful statistical tool for examining multivariate data with complicated interactions between variables (Kline, 2016; Yanuar, 2016; Yanuar, 2016). SEM is also a statistical method for putting a conceptual or theoretical model to the test. Confirmatory factor analysis, path analysis, path modeling, and latent growth modeling are all part of SEM. SEM may be used to investigate the relationship between numerous measures and latent structures, which is one of its key advantages. It also works with cross-sectional and longitudinal data, as well as experimental and non-experimental data. In multivariate analysis of a structural theory that predicts causal links between numerous variables, SEM uses a confirmatory (hypothesis testing) technique (Suh, 2015; Yanuar, 2015).

The normalcy assumption for error and the degree to which models are adequately stated are two crucial features of SEM. Different estimating approaches, such as weighted least squares (WLS) and diagonally weighted least squares (DWLS), provide estimates that converge to the same optimum and have similar asymptotic features, which may be deduced analytically (Isnayanti, 2019; Li, 2016; Newsom and Smith, 2020) when both assumptions are fulfilled under ideal conditions (DiStefano and Morgan, 2014; Mîndrilă, 2010). As a result, the technique selection is arbitrary. Olsson et al. (2000) proved that standard errors of parameter estimates could be considerably underestimated by Maximum Likelihood (ML) and Generalized Least Square (GLS) when categorical data was used. They discovered that the quantity of misspecification has an impact on the underestimating of ML and GLS standard errors when compared to DWLS. Estimated standard errors for WLS tend to be more realistic than for GLS for substantially misspecified models. The purpose of this study is to compare the performance of WLS and DWLS in constructing the acceptable model of Health Behavior in West Sumatera. The individual in good health behavior tends to avoid the spread of the COVID-19 virus (Arora and Grey, 2020; Eaton and Kalichman, 2020). West Sumatera is one province with the highest cases of Covid-19 in Indonesia. Thus, this study will investigate the factors of health behavior for individuals living in West Sumatera.

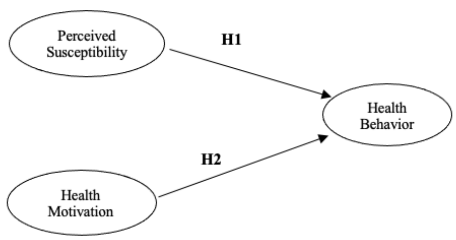

Figure 1. The Hypotheses Model of Health Behavior

2. EXPERIMENTAL SECTION

2.1 Materials

The health behavior model is based on the idea of predicting health-related behavior based on particular thought patterns. The health behavior model can also be interpreted as a theoretical construct regarding individual beliefs in healthy behavior (Sillice et al., 2014). This healthy behavior can be in the form of preventive behavior or the use of health facilities. Khoso et al. (2016) wrote that Health behaviors are influenced by Health belief factors that can form healthy living behaviors to avoid the transmission of infectious diseases. As a result, the model is utilized to describe and forecast both preventive health behavior and sick-role and sickness behavior. Knowledge, motivation, and attitudes regarding the psychological barriers to action, the efficacy of alternative activities, perceived self-efficacy, perceived vulnerability, and interpersonal factors have all been demonstrated to impact an individual's decision to adopt a healthy behavior (Karimy et al., 2017).

In this study, the indicators for measuring Health motivation are eagerness or motivation to avoid: touching the face, shaking hands, meeting or standing in long queues, touching objects in public areas, taking public transportation (online), going home, worshiping in mosque/church/others and ordering online food. One's perception of the risk or likelihood of getting a health ailment or condition is referred to as perceived susceptibility. A person's feelings of personal vulnerability to an illness or disease might vary greatly (Karimy et al., 2017). The operational indicators for measuring Perceived susceptibility in this study are worried about/when: personal health, the health of their family members, going outside, going to school/work, using public facilities/public transportation, food availability, and spreading of an infectious disease. All indicator variables are in 5 Likert scale or ordinal type. This study assumes that Health motivation and Perceived susceptibility are factors influencing Health behavior. The assumption is used to construct the hypothesis model as provided in Figure 1.

The hypothesis model then fitted to the data set regarding the health behavior of individuals living in West Sumatera. The primary data used in this study was obtained by distributing the online questionnaires. The questionnaires were distributed from March to May 2020. All 756 respondents with complete information were involved in the analysis from more than 1000 respondents who participated in filling the questionnaire. The questionnaire consists of three parts, i.e., Health behavior, Perceived susceptibility, and Health motivation.

2.2 Methods

Number SEM combines two types of equations simultaneously. Those are structural equations and measurement equations. The measurement equation is explaining the relationship between the indicator variable to its latent variable, which is formulated as follows (Eq.1):

$$\mathrm{x} = \Lambda\omega + \varepsilon, \tag{1}$$

where x is an m×1 vector which represents indicator variable describing the q×1 latent vector ω, Λ is m×q matrix of the loading factors and ε is m×1 random vector of the measurement error. Meanwhile, the structural equation is the interrelationship among the latent factors and formulated by Eq.2:

$$\eta = \Gamma\xi + \delta. \tag{2}$$

Let the latent variable ω be partitioned into (η,ξ) where η and ξ are latent variables, respectively. The parameter η is $q_1\times1$ endogenous latent variable which is, in this case, is Health behavior and ξ is $q_2\times1$ exogenous latent variables, i.e., Health motivation and Perceived susceptibility. Then, Γ is $q_1\times q_2$ matrix of loading factors relating the exogenous latent variables to the endogenous latent variable, and δ is $q_1\times1$ random vector of structural error.

The next SEM analysis estimates the population parameter based on the model specification component performed above. The goal of estimation is to minimize the difference between the hypothesized matrix which is represented by a function of parameter θ, a vector that includes all the unknown parameters, $\theta=\{\Lambda, \Gamma\}$, denoted as $\Sigma(\theta)$ and the sample covariance matrix, denoted as S. The fitting function, denoted by $F(S,\Sigma(\theta))$ is utilized to measure the closeness between these two variance-covariance matrices S and $\Sigma(\theta)$. In this study, two estimation methods, Weighted Least Square (WLS) and Diagonally Weighted Least Square (DWLS) (Flora and Curran, 2004) are applied to estimate the parameter model with indicator variables are in categorical type.

The distribution of all observed random variables must be specified in this estimation procedure. Because the outcomes are continuous, it is common to assume that all random variables follow a normal distribution. The MLE method estimates parameters, its standard error, and fit indices using a normal distribution for all parameter models based on elements matrix derived from the asymptotic variances of the thresholds and latent correlation estimates. MLE based on sample product-moment correlation or covariance matrix among ordinal indicator variables fails miserably (Flora and Curran, 2004; Rahmadita et al., 2018; Yanuar, 2015). In particular, standard error estimates tend to be incorrect, parameters are

Table 1. The Highest Responses for Each variable.

No	Variables	Categories	Percentages (%)
	Health Motivation		
1	Avoid touching the face	Sometimes	36.9
2	Avoid shaking hands	Always	53.6
3	Avoid meeting or standing in long queues	Always	43.5
4	Avoid touching objects in public areas	Often	32.4
5	Avoid taking public transportation (online)	Always	59.1
6	Avoid going home	Always	59.1
7	Avoid worshiping in mosque/church/others	Always	52.6
8	Avoid ordering online food	Always	35.7
	Perceived Susceptibility		
9	Personal health	Not worried	42.3
10	The health of their family members	Not worried	50.9
11	When they go outside	Not worried	54.9
12	When they are going to their village	Not worried	62.8
13	To work/school, public facilities / public transportation	Not worried	59.8
14	Food availability	Not worried	42.1
15	Spreading of an infectious disease	Worried	53.5
	Health Behavior		
16	Keep a distance of 2 m	Often	39
17	Put on a mask	Always	54.8
18	Hand sanitizer	Always	43.8
19	Wash hands for 20 seconds	Always	46
20	Inform others if having symptoms of a disease	Always	52.2

underestimated, the chi-square model fit statistics are inflated (Hutchinson and Olmos, 1998). Therefore, the WLS approach is employed to estimate a weight matrix based on the asymptotic variances and covariances of polychoric correlation in the estimation of the SEM model (Flora and Curran, 2004). The polychoric correlation is used to estimates the linear relationship between two unobserved continuous variables given only observed ordinal data (Bollen and Maydeu-Olivares, 2007).

WLS applies the fitting function

$$F_{WLS} = (s - \sigma(\theta))W^{-1}(s - \sigma(\theta)), \tag{3}$$

where **s** is a vector of sample statistics (i.e., polychoric correlations), $\sigma(\theta)$ is the model-implied vector of population elements in $\Sigma(\theta)$, and W is a positive-definite weight matrix. Muthén and Muthén (2017) suggested a robust WLS approach by substituting a diagonal matrix, V for W in Equation (3). Elements of V are the diagonal elements of the original weight matrix W. Calculation of this matrix involves the full weight matrix of W but it is not inverted. Complete discussion regarding WLS and DWLS estimator in SEM model has been explained in (Flora and Curran, 2004). This present study implements Mplus software to estimate parameter models using WLS and DWLS (known as WLSMV in Mplus) estimation methods (Yanuar, 2016; Yanuar et al., 2010).

The following step is model evaluation of sample parameters, which is done when the estimated parameters have been collected. A measure of overall fit, an evaluation of the solution, and a comprehensive assessment of fit are all required for the estimation of fit. To begin, parameter estimates with the appropriate size and sign, parameter estimate correlations, standard errors within suitable ranges, and coefficient determination are usually employed to ensure that each variable is appropriate. The total model fit is next checked to see if the given model matches the data properly. The indicators of goodness of fit to check the overall model fit are RMSEA, CFI, and TLI (Yanuar et al., 2010). Mplus provides the results of the model fit indicators. The RMSEA is an absolute fit indicator that measures how close a hypothesized model is to be perfect. CFI and TLI, on the other hand, are incremental fit indices that compare the fit of a proposed model to a baseline model (i.e., a model with the worst fit). A set of cut-off criteria is strongly reliant on the application of RMSEA, CFI, and TLI. An RMSEA value of 0.05 implies a close fit, whereas 0.08 represents a fair model-data fit, according to several research types. A TLI value of more than 0.90 suggests a good fit. However, rather than statistical justification, these recommendations are mostly based on intuition and experience (Xia and Yang, 2019; Yanuar, 2016).

3. RESULTS AND DISCUSSION

In the conceptual model, it was hypothesized that the exogenous latent variables Perceived susceptibility and Health moti-

Table 2. The Results for Health Behavior Model Using SEM

No	Items	Estimate (Standard Error) DWLS	WLS	R^2 (in %) DWLS	WLS
A	**Structural Equation**				
	Perceived Susceptibility → Health Behavior	0.114* (0.036)	0.139* (0.027)		
	Health Motivation → Health Behavior	0.737* (0.028)	0.809* (0.020)	57.6	72.7
B	**Measurement equation**				
	Health Motivation				
1	Avoid touching the face	0.630* (0.026)	0.751* (0.018)	58.2	64.5
2	Avoid shaking hands	0.788* (0.019)	0.853* (0.013)	39.6	56.4
3	Avoid meeting or standing in long queues	0.860* (0.015)	0.917* (0.010)	62.1	72.7
4	Avoid touching objects in public areas	0.840* (0.014)	0.888* (0.009)	74	84.1
5	Avoid taking public transportation (online)	0.789* (0.021)	0.883* (0.014)	62.2	78.9
6	Avoid going home	0.659* (0.028)	0.723* (0.019)	43.5	77.9
7	Avoid worshiping in mosque/church/others	0.673* (0.025)	0.740* (0.018)	45.3	52.2
8	Avoid ordering online food	0.560* (0.027)	0.647* (0.020)	31.3	54.7
	Perceived Susceptibility				
9	Personal health	0.921* (0.010)	0.943* (0.006)	84.8	41.8
10	The health of their family members	0.930* (0.009)	0.966* (0.006)	86.5	89
11	When they go outside	0.827* (0.014)	0.916* (0.009)	68.4	93.3
12	When they are going to their village	0.744* (0.021)	0.877* (0.013)	55.4	83.9
13	To work/school, public facilities / public transportation	0.808* (0.017)	0.907* (0.010)	65.4	77
14	Food availability	0.510* (0.027)	0.605* (0.020)	26	82.4
15	Spreading of an infectious disease	0.550* (0.027)	0.648* (0.020)	30.3	36.6
	Health Behavior				
16	Keep a distance of 2 m	0.763* (0.024)	0.803* (0.017)	58.2	64.5
17	Put on a mask	0.138* (0.049)	0.106* (0.034)	1.9	1.1
18	Hand sanitizer	0.513* (0.033)	0.559* (0.023)	26.3	31.2
19	Wash hands for 20 seconds	0.641* (0.032)	0.737* (0.021)	41	54.3
20	Inform others if having symptoms of a disease	0.601* (0.034)	0.608* (0.023)	36.1	36.9

*Significant at level 0.05

Table 3. The Goodness of Fit for Both Estimator

Indicator GOF	DWLS	WLS
RMSEA	0.077	0.081
CFI	0.952	0.965
TLI	0.945	0.96

vation give effect to Health behavior. Seven indicator variables are assumed to measure Health motivation, and eight indicators to measure Perceived susceptibility. Health behavior is assumed measured by five indicator variables. All indicator variables are in ordinal type with five Likert scales. The responses of all indicator variables for Health Motivation and Health behavior are 'never' coded into 1, 2 as 'rarely', 3,4 and 5, referring to 'sometimes', 'often', and 'always', respectively. Meanwhile, all indicator variables for measuring Perceived health are coded as 1, 2, 3, 4, and 5 referring to 'not worried at al', 'not worried', 'little worried', 'worried', and 'very worried'. Table 1 presents the information of the highest percentages of responses in each indicator variable obtained based on the primary data.

The next analysis is fitting the hypothesis model to the data using both estimator methods, WLS and DWLS. Table 2 presents the estimated values for structural and measurement loading factors and their corresponding standard error. This table informs us that Perceived susceptibility statistically significant to give effect to Health Behavior with a loading factor is 0.114 using DWLS and 0.139 based on the WLS method. Meanwhile, the effect of Health motivation on Health Behavior using DWLS is 0.737 and with WLS is 0.809. This value is statistically significant. The standard errors yielded from WLS are slightly smaller than DWLS in these structural equations.

This study found that all indicator variables are significant in measuring the respective latent factors, as indicated by the * in the measurement equation. From columns two and three, it is concluded that all loading factors used DWLS is smaller than WLS; meanwhile, its corresponding standard errors based on DWLS are higher than WLS. This table also presents the coefficient determination or R^2 for each equation based on both estimator methods. It's also concluded that R^2 from the WLS method resulted in higher than DWLS. It means that the proposed model obtained from the WLS estimator is better than DWLS. Based on these results, it informs us that WLS yields better-estimated values than DWLS.

After obtaining the estimated values for each loading factor, the goodness of fit for each estimator method is calculated. Table 3 presents the result for both estimators.

Table 3 shows that the RMSEA value from DWLS is 0.077 (acceptable), but the value from WLS is 0.081, which is on the borderline because the range of allowable RMSEA values is less than 0.08 (Chen et al., 2008). The CFI and TLI values from DWLS are 0.952 (> 0.95) and 0.945 (on the borderline). The CFI and TLI values based on WLS are 0.965 and 0.960; both values are > 0.95 or within the acceptance range. From this result of the goodness of fit for both models, we could conclude that both proposed models are a good fit and could be accepted.

4. CONCLUSIONS

Using the DWLS estimation method in categorical data in which normality assumption is violated will result in a higher value for standard deviation than the WLS estimation method. As well as in terms of the goodness of fit for model obtained based on DWLS method result lower value than WLS method. The coefficient determination for each model (structural and measurement equations) also shows that the DWLS model tends to have a lower value of R^2 than the WLS model. Three indicators of the goodness of fit model, i.e., RMSEA, CFI, and TLI, also estimated in this present study, yield the same conclusions. For future work, we suggest doing a comparison between WLS and DWLS methods with other estimation methods, such as Two-stage least square (2SLS), Bayesian method, etc.

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