CSCanada
Canadian Social Science
Vol. 8, No. 5, 2012, pp. 71-78
DOI:10.3968/j.css.1923669720120805.1148

ISSN 1712-8056[Print]
ISSN 1923-6697[Online]
www.cscanada.net
www.cscanada.org

The Modification of Dichotomous and Polytomous Item Response Theory to Structural Equation Modeling Analysis

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Supported by The Promotion of Research in Higher Education Project, Faculty of Education Mahasarakham University, 2011-2012.

Received 2 August 2012; accepted 8 Ocotber 2012

Abstract

The objective of the present research was to make modifications to Structural Equation modeling analysis by Dichotomous and Polytomous Item Response Theory (SEDPIRT) which consisted of 4 stages of 1) The development of structural equation modeling analysis, 2) Data simulation for analysis, 3) Verification and comparison of analysis results through the SEDPIRT with Path Analysis by LISREL (PAL) using data simulation and 4) trying-out SEDPIRT analysis with empirical data.

The study resulted in a structural equation modeling analysis SEDPIRT in which a person's true ability and attributes obtained from Item Response Theory (IRT) analysis is used for observable variables. It is assumed that such observable variables are latent with no measurement deviation for use as the data for assessing path coefficients and structural equation modeling analysis. The SEDPIRT measurement is valid and would not deviate because of changes in the tests or test takers. A verification of an analysis of simulation data showed that standard error in the estimation of every paths coefficient (P_{ij}) and the iteration of P_{ij} by SEDPIRT analysis is significantly less than the PAL at the .01 level of significance and the root mean squared residuals of SEDPIRT and PAL are not significantly different, although the SEDPIRT analysis yields a model with greater validity than the PAL at the .01 level of significance. The SEDPIRT analysis model shows a model validation of 97.50 % while the PAL one shows 77.50%, and all path coefficients of the SEDPIRT and PAL are positively correlated at the .01 level of significance.

It was found from applying the two techniques to empirical data that standard error in the estimation of all the path coefficients, the root mean square residual of the deviation, the number of iteration and the adjustment count in an attempt to make the two models consistent with empirical data in the SEDPIRT are less than the PAL; the Goodness-of Fit Index (GFI) and the Adjusted Goodness-of Fit Index(AGFI) in the SEDPIRT are more than the PAL; and path coefficients of the SEDPIRT and PAL show a positive correlation at the .01 level of significance with a Pearson-product moment correlation coefficient of .869.

Key words: Structural equation modeling analysis by Dichotomous and Polytomous Item Response Theory (SEDPIRT); Path analysis by LISREL (PAL); Grade-Response Model (GRM); Three parameter logistic model

Terdsak Suphandee,Yannapat Seehamongkon, Suntonrapot Dumrongphanit, Wirat Phongsiri (2012). The Modification of Dichotomous and Polytomous Item Response Theory to Structural Equation Modeling Analysis. *Canadian Social Science, 8*(5), 71-78. Available from http://www.cscanada.net/index.php/css/article/view/j.css.1923669720120805.1148
DOI: http://dx.doi.org/10.3968/j.css.1923669720120805.1148.

INTRODUCTION

Path analysis is a technique developed by the English biologist Sewell Wright for studying direct and indirect causes of variables under study. It is a technique that is not only for finding out causes and effects but also for testing relationship between theories developed by a researcher as a primary causal model. It is used for affirming or supporting the belief that which independent variables cause variations or differences in the dependent variables, and whether the causes directly or indirectly derive from the particular independent variables by joining with other variables to cause variations in the dependent variables.

It is truly a profound knowledge that sheds new light on path analysis (Randall & Richard, 1996, pp.5-6).

One major problem with the existing model of path analysis is the use of confirmatory factor analysis (CFA) whereas such model is still based on the theory of model analysis which treats factor scores as true scores in the classical test theory (X = T + E). Such practice has also inadvertently caused limitations to the analysis of any variables in the context of classical test theory. This is particularly true when the variables in the model are latent and can be measured by using either a test or scales, and the marking practice is varied, i.e. assigning 1 mark for each correct answer and 0 for the false one, or assigning scores basing on rating scales that have been used. As these variables are latent and direct measurement cannot be done it usually causes the scores made by test takers to be dependent on the test or scales used. This is due to the fact that when a test or a set of scales with a difficulty index, a discrimination power and reliability of its own, is used for measuring a pair of variables from a sample and it usually results in one set of measurement scores or true scores. If one tries to compare the causal relationship between one pair of variables by using the results of an analysis of each, a certain causal relationship would be found. Later on, if another set of test with different difficulty index and discrimination power, is used for analyzing the same pair of variables obtained from the same group of sample, the resulting scores or true scores can be deviated and would inevitably affect the causal relationship between the pair. It is evident, therefore, that a different test usually gives different true scores. Besides, traditional testing model usually gives non-parameter testing scores or true scores that do not represent the true qualities of each individual test taker. Instead, it rather shows a quality of a test taker which deviates in accordance with the characteristics of the test he takes. In addition, the principle of assessing deviation inheres in the traditional testing model would usually give only one measuring deviation for each variable, and as such, an estimated deviation is constant for everyone in the sample group (Kanjanawasri, 2007, p.7). Because of the foregoing problems a new mode of measurement has been introduced which provides reliability and validity that do not alter even with changes in the test, the questionnaire and the test-taking group. It is called the Item Response Theory or IRT. The purpose of testing, according to the IRT, is to assess the takers' trait in relation to their answering the test, the characteristics of the test and the probability of answering the test so that the results can be used to indicate the rank of takers on a continuous trait line called Item Characteristic Curve or ICC. The IRT thus has enabled researchers to assess how suitable and effective a test is (Baker, 1992, pp.1-23; Embretson & Reise, 2000, pp.3-9; Fischer & Molenaar, 1995, pp.3-14). That is to say, when the IRT Model fits in with the data there will not be change in the parameter of the test and the parameter of test takers' ability.

Muthen argued that the CFA and IRT models don't just have some connections -- they are the same. So the process from the assessment model that uses CFA technique for verifying latent variables that same if we use Item Response Theory is used instead for assessing true ability score of each test taker in the sample group. The true ability scores, or true scores according to the classical test theory, can be analyzed for assessing path coefficient in the structural equation model instead of applying factor scores for analysis as has been a prevailing trend at the present. The practice of applying true scores for assessing path coefficient would be more than likely to result in a new path analysis model which consists of two parts, i.e. 1) the assessment model that applies the item response theory for assessing each test taker's true ability and 2) a structural equation model that can be used for estimating path coefficient through the Maximum Likelihood Estimation which is regarded as a highly reliable technique by statisticians in general.

There is a major limitation in the Dichotomous IRT Model in that when marking each answer in a test the mark assigned to either 1 or 0. Such is the case of a true-false or agree - not agree test. However, there are several other educational or psychological testing instruments that assign different marks to each test item. The practice possibly arises from a belief that the test provides greater information and therefore causes the test taker to feel more confident than doing the dichotomous-type of test. These polytomous include attitude test, characteristic test, vocational interest test, etc. that assign more than 2 marks to each questionnaire item. In this study the present researcher has opted for Graded-Response Model (GRM) simply because it is the type of test or questionnaire that emphasizes discrimination power. Besides, it is a well-known model that has been developed from 2-parameter model logistics that contain different discrimination power in each of the test items (Dodd, Ayala & Koch, 1995, p.11)

Because of the foregoing reasons regarding the problem of solving the deviation in the latent variables, the problem of applying Item Response Theory, the problem of variable characteristics in a model and the levels and testing of latent variables the present researcher has become interested in modifying the dichotomous and polytomous IRT in his analysis of structural equation modeling which he calls the SEDPIRT. It's his attempt to propose a new option for statistical analysis that aims at studying causal relationship between variables without deviation. It's his belief that SEDPIRT will provide more reliable analysis results that can effectively explain causal relationship between variables. He'll compare results of his analysis of the modified Structural Equation Model with that of the Path Analysis by LISREL or PAL for the purpose of verifying the effectiveness and reliability of SEDPIRT.

PURPOSES OF THE STUDY

1. To modify dichotomous and Polytomous IRT Model of Item Response Theory in Structural Equation Modeling Analysis;

2. To verify results from analyzing the SEDPIRT and PAL Structural Equation Models by using 40 sets of simulation data which consist of standard error of estimation in the assessment of P_{ij}, the difference in the number of iterations in the assessment of P_{ij}, the difference in the Root Mean Squared Residual (RMR) and the proportions of models with validity after the analysis. (first run)

3. To study the SEDPIRT and PAL methods of analysis with empirical data.

PROCEDURES

The study was conducted in accordance with Research and Development method consisting of 4 stages below.

Stage I: The Development of SEDPIRT

At this stage the present research applied the following techniques in his attempt to synthesize related documents:

1. Compiling and reviewing literature and research works which were related to Structural Equation Model and the Dichotomous and Polytomous Model of Item Response Theory in order to develop ideas for constructing a new analysis model;

2. Constructing a new Structural Equation Modeling Analysis by modifying the SEDPIRT the model of which is shown in Figure I below.

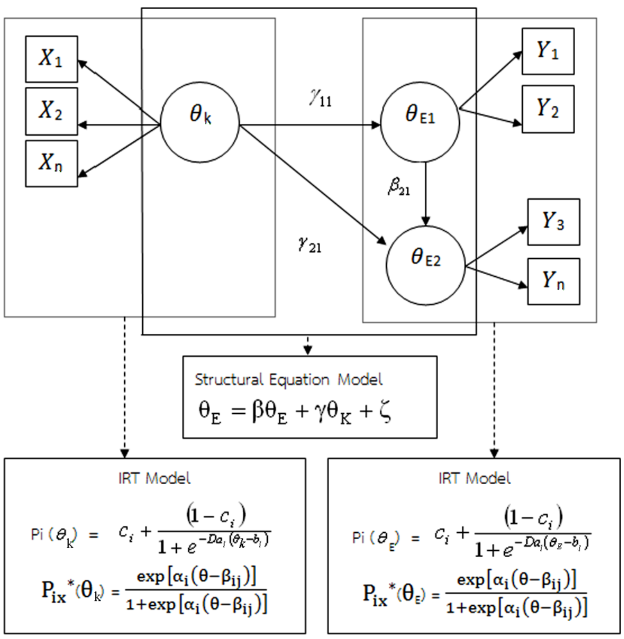


Figure 1
The SEDPIRT Model

Stage II: Data Simulation for Analyzing Structural Equation Model

At this stage a model was developed according to the hypothesis that has been put forward basing on the data on theories and research works gathered from review of literature relating to learning achievement. The model was comprised of 5 latent variables and each of the variables contained 10 observable variables.

The development of the model started with preparing 40 sets of simulation data by means of a Wingen 3 Program which is capable of identifying and distributing test takers' true ability scores. This is done for 2 reasons of 1) a repeated trying out of the 40 sets of simulation data which were obtained from synthesizing results of research works based on Monte Carlo Technique for testing significances (Shanghai, 1991) and 2) a comparison of analysis results of the SEDPIRT and PAL Structural Equation Models which are used for testing significances in order to compare each pair's statistical value. That's the reason for using 40 sets of samples which were determined according to the proportion of samples to variables at 20:1 (Linderman, Merenda, & Gold, 1980, p. 163).

Having done the foregoing activities the researcher went further to elaborate on the model as follows:

1. To determine the parameter of all the latent variables of true ability scores of the sample group so that it shows a normal distribution with a mean score of 0 and a standard deviation of 1;

2. To determine the parameter of the tests as follows:

2.1 For a 3-Parameter Logistics Model in which 1 or 0 marks were given to each of the answers, Parameters a and b have a normal distribution, $\overline{X} = 0.5$, S.D. = 1, and Parameter c was also with a normal distribution but $\overline{X} = 0.2$ and S.D. = 0.1.

2.2 For the Grade-Response Model a rating scale of 5, 4, 3, 2, 1 scores was used to determine the weight of each of the responses and the $\overline{X}$ and S.D. of both Parameters a and b were at 0.5 and 1. The data used for simulation were the raw scores resulting from administering the test in which basic statistics were used to determine arithmetic mean, standard deviation, inter- correlation coefficient and an exploratory factor analysis to test unidimensionality of the observable variables in each of the latent variables, in which case the eigen value of the first composite part must be higher than the remaining parts (Boonruangrat, 1997, p.7).

Stage III: Verification of the Results of Analyzing SEDPIRT in Comparison with PAL

Activities at this stage were done in the following steps:

1. Analyzing the SEDPIRT and PAL Models in which 40 sets of simulation data were used for each of the model but with different method.

1.1 The analyzed PAL that used the simulation data from samples are tests (which 1 or 0 marks: mathematics learning achievement and prior knowledge) and questionnaire (a rating scale of 5, 4, 3, 2, 1 scores: learning intention, achievement motivation and attitude towards mathematics) for input this data to analyze by LISREL program all at once (Used LISREL program).

1.2 The SEDPIRT used the simulation data from samples, that the test analyzed by dichotomous IRT, questionnaire analyzed by polytomous IRT (used IRT program;Multilog) for estimate true ability or trait in the first step then the second used data from the first is è of every samples to analyzed by PAQ technique (Used LISREL program).

2. Comparing the differences in the dependent variables derived from analysis of the two models using dependent sample t-test which was consisted of standard error of estimation in the path coefficient, the number of iteration of P_{ij} and the Root Mean Squared Residual.

3. Comparing the proportions of the models with validity after an analysis of the data obtained from the first run of the Program and using percentage.

4. Identifying the relationship between P_{ij} of the two models through Pearson Product-Moment Correlation Coefficient.

Stage IV: Trying-out of the SEDPIRT with Empirical Data. This stage consisted of the following steps

1. Construction of the model by way of synthesizing theories and results of a research study on learning achievement in mathematics. Five latent variables were included in the model, i.e. 1) mathematics learning achievement scores which were assessed from 3 observable variables of computing skill, understanding skill and problem solving skill; 2) prior knowledge which were assessed from 3 observable variables of computing skill, understanding skill and problem solving skill; 3) learning intention which were assessed from 3 observable variables of learning concentration, learning interest and learning attention; 4) achievement motivation which were assessed from 5 observable variables risk, enthusiastic, responsibility, knowledge of decision and prediction and 5) attitude towards mathematics which were assessed from 3 observable variables of intelligence, position sense and practice.

The empirical data used in this study obtained from a research work by Kampoogeo (2010) which developed a structural equation model which affects learning achievement in mathematics of grade 6 students in Udonthani Province. The data collected from 827 samples. We used the answering tests and questionnaires of 827 samples were used to analysis between the two models of SEDPIRT and PAL based on the empirical data that verify and compare the methods.

2. Analyzing the structural equation models of SEDPIRT and PAL.

3. Adjusting the models in case they were not consistent with the empirical data.

4. Comparing results of the analysis of the 2 models on the aspects of standard error of estimation in the assessments of P_{ij}, the Chi-square, the probability that resulted from deviation in p-value, test of validity by means of Chi-square, Root Mean Square Residual, Goodness of Fit Index and Adjusted Goodness of Fit Index.

RESULTS

SEDPIRT is a model that shows causal relationship between latent variables with a basic principle that the causal structure consisting of causal relationship between latent variables within the independent as well as dependent variables. These latent variables are not observable but can be assessed through the Item Response Theory Model. Such assessment was made by means of calculating the test takers' responses to the test using both dichotomous and polytomous scales. Results of the study were two models with their specific characteristics as follows:

1. IRT Measurement Model

The IRT model assesses True ability score of each sample. The score is then used for analyzing path coefficient.

2. Structural Equation Model

The structural equation model indicates causal relationship between latent variables. The latent variable and are true ability scores of the test takers obtained through an assessment by IRT Model in which is assigned Latent Endogenous Variable is assigned latent exogenous variables as in the following equation:

$$\theta_E = \beta\theta_E + \gamma\theta_K + \zeta$$

When θ_K represents vector of the latent dependent variable represents vector of the latent independent variable

(Beta) represents matrixes of regression coefficient which shows direct influence of θ_{Ej} on vectors θ_{Ei} of other latent dependent variables

(Gamma) represents matrixes of regression coefficient which shows influence of θ_k on vectors θ_E of other latent dependent variables

ζ(Zeta) represents vectors of deviation

Results of SEDPIRT Analysis Compared with PAL Using Simulation Data

1. Standard error of mean in estimated path coefficient from the analysis of the structural equation modeling of SEDPIRT was smaller than the standard error of mean in estimated path coefficient from the structure equation modeling of PAL at the .01 level of significance eight paths.

2. Comparing the differences of the calculation of iteration from the estimated parameter between the results of both SEDPIRT and PAL structure equation modeling were presented in Table 1.

Table 1
$\overline{X}$, S.D. and T-Value in the Test of Iteration Differences Between SEDPIRT and PAL Analyses

Analysis methods	n (sets)	$\overline{X}_{It}$	$S.D._{It}$	t
SEDPIRT	40	0.00000	0.00000	14.924**
PAL	40	12.9000	5.46692	

From Table 1 the number of iteration of SEDPIRT structural equation model was significantly smaller than the method used analyzed PAL structural equation modeling at the significant level of .01. Iteration of

SEDPIRT analysis was 0 every set data but PAL's iteration every set data had mean equal 12.9 rounds.

3. Root Mean Square Residuals (RMR) of SEDPIRT model and PAL model were not different.

4. Comparison of Proportion validation model after analyzing with 40 data sets between SEDPIRT with PAL are presented in Table 2

Table 2
Comparison of Proportion validation model after analyzing with 40 data sets between SEDPIRT with PAL

Analysis methods	n (sets)	Results		Percentage of valid models	Z
		Valid	Invalid		
SEDPIRT	40	39	1	97.50	3.20**
PAL	40	31	9	77.50	

(Validation model are considering that all reported model fit indices of a good model fit : CFI > .95, RMSEA < .05, SRMR < .06 and p-value >.05)

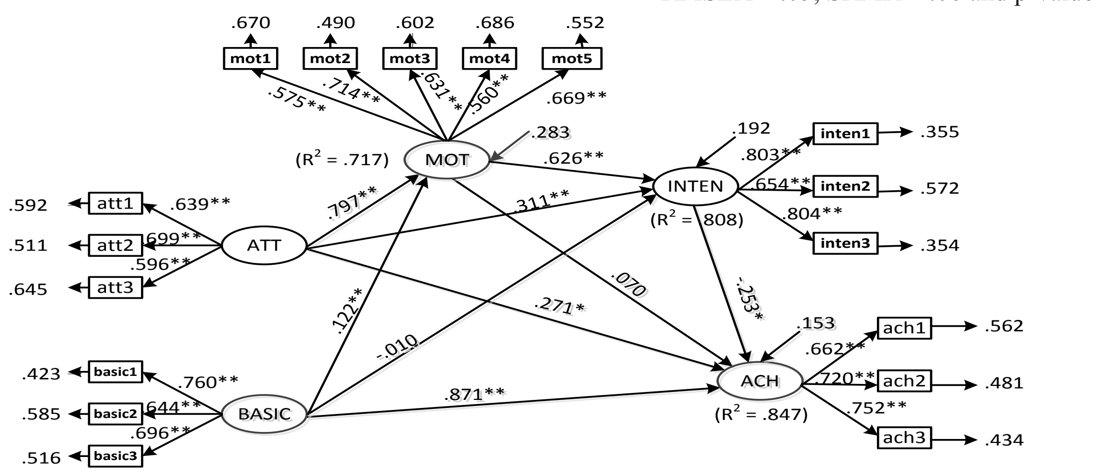
As presented in Table 2, SEDPIRT analyzing technique gave the better valid model than the PAL analyzing technique at the .01 level of significance. In addition, SEDPIRT method resulted in 39 valid models (97.5%, $p < .05$), while 31 valid models (77.5%, $p < .05$) were obtained from PAL method

5. Path coefficients (P_{ij}) between SEDPIRT and PAL analysis methods were positively related at the .01 level of significance in every path. There was one path that very height, height 6 paths and Moderate 1 path.

Results of structural equation modeling of PAL and SEDPIRT with empirical data

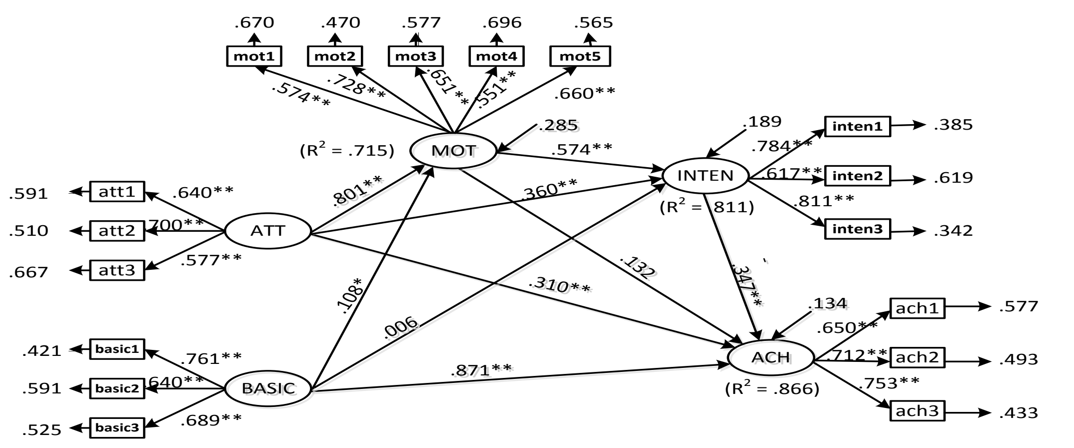
1. Fitting the PAL model with empirical data

The result of the analysis using the PAL technique to fit the causal model of variables influencing Mathematics learning outcome with empirical data is presented in Figure 2. (validation model are considering that all reported model fit indices of a good model fit : CFI > .95, RMSEA < .05, SRMR < .06 and p-value >.05)



Chi-Square = 261.68, df = 109, p-value= 0.0000, CFI=0.987, AGFI=0.950, RMSEA=0.041, SRMR = 0.0339, R^2= .847

Figure 2
The Result of PAL Technique Round 1



Chi-Square = 116.07, df = 93, p-value= 0.05297, CFI=0.998, AGFI=0.973, RMSEA=0.017, SRMR = 0.0252, R^2= .866

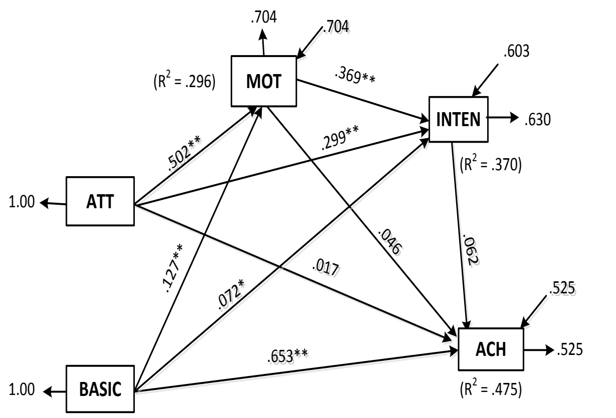
Figure 3
The Final Model of Mathematics Learning Outcome Using PAL Technique of Analysis

As presented in Figure 2, the casual model of Mathematics learning outcome, analyzing with the PAL technique round 1 was not good fit to the empirical data, Chi-Square = 261.68, df = 109, CFI=0.987, AGFI=0.950, RMSEA=0.041, SRMR = 0.0339, R^2= .847, and p-value = 0.0000. Thus, the researcher adjusted the casual model as suggested by the model modification indices. Additional parameters were added one at the time until the model had good fit.

For this model, it had been modified for 16 times by adding the error correlation of TH(3,2), TH(3,3), TE(8,3), TE(7,6) TH(6,11), TE(10,9), TE(3,2), TH(6,9), TE(5,4), TH(2,4), TE(10,1), TH(3,7), TE(11,10), TD(5,3), TH(5,7), TH(3,1). The adjusted model was fit well to the empirical data with Chi-Square = 116.07, df = 93, CFI=0.998, AGFI=0.973, RMSEA=0.017, SRMR = 0.0252, R^2= .866 and p-value= 0.05297. The final adjusted model is presented in Figure 3.

2. Fitting the SEDPIRT model with empirical data

The result is presented in Figure 4 (validation model are considering that all reported model fit indices of a good model fit : CFI > .95, RMSEA < .05, SRMR < .06 and p-value >.05)



Chi-Square = 0.00, df = 1, p-value= 1.00, CFI=1.00,AGFI=1.00, RMSEA=0.00, SRMR = 0.00,
R^2= .475

Figure 4
The Result of SEDPIRT Technique Round 1

The structural model of Mathematics learning outcome round 1 was analyzed with the SEDPIRT technique. As presented in Figure 4, the model demonstrated good fit with the empirical data, Chi-Square = 0.00, df = 1, CFI=1.00, AGFI=1.00, RMSEA=0.00, SRMR = 0.00, R^2= .475 and p-value= 1.00.

3. All 9 standard errors of estimated path coefficient from the SEDPIRT model were smaller than those of estimated path coefficient from the PAL model.

4. Comparison of statistics values and goodness of fit statistics are presented in Table 3

Table 3
Comparison of Statistics Values and Goodness of Fit Statistics

Statistics Values and Goodness of Fit Statistics	Analysis Methods	Results	Comparison
p-value	SEDPIRT	1.000	SEDPIRT > PAL
	PAL	0.053	
Root Mean Squared Residual (RMR)	SEDPIRT	0.000	SEDPIRT < PAL
	PAL	0.024	
Goodness of Fit Index (GFI)	SEDPIRT	1.000	SEDPIRT > PAL
	PAL	0.984	
Adjusted Goodness of Fit Index (AGFI)	SEDPIRT	1.000	SEDPIRT > PAL
	PAL	0.973	

The results in Table 3 showed that p-value of model validation with Chi-square, Goodness-of Fit Index (GFI) and Adjusted Goodness-of Fit Index (AGFI) of the SEDPIRT were larger than those of the PAL techniques, while Root Mean Squared Residual (RMR) of the SEDPIRT technique was smaller than the PAL technique.

5. Numbers of iterations and model modifications from SEDPIRT technique were lower than PAL technique. The number of iteration in SEDPIRT technique was 0, while the numbers of iterations of PAL model were 25. Moreover, SEDPIRT model was good fit to the empirical data without any adjustment or modification, while PAL model required 16 modifications before the model fit well to the data.

6. The results of correlation coefficients between the path coefficients, SEDPIRT with PAL is presented in Table 5

Table 5
The Test of Correlation Coefficients Between the Path Coefficients, SEDPIRT with PAL

P_{ij} values	Analysis Methods	
	SEDPIRT	PAL
PACH-BASIC	.653**	.871**
PINTEN-BASIC	.072*	.006
PMOT-BASIC	.127**	.108*
PACH-ATT	.017	.310**
PINTEN-ATT	.299**	.360**
PMOT-ATT	.502**	.801**
PACH-INTEN	.062	-.347**
PACH-MOT	.046	.132
PINTEN-MOT	.369**	.574**

Correlation coefficients between the path coefficients ($r_{SEDPIRT-PAL}$) = 0.869**

As presented in Table 5, the path coefficients of the SEDPIRT and PAL show a positive correlation at the .01 level of significance with a Pearson-product moment correlation coefficient of .869.

DISCUSSION

Our findings suggested that Item Response Theory can be applied and used with structural equation modeling analysis because the SEM technique that is currently using is consisted of 2 important parts: Measurement model and Structural Equation Model. These two parts are crucial, especially in analysis of models with latent variables. In the past, the Classical Structural Equation Model Analysis was unable to be used to analyze the SEM with latent variables and therefore have to measurement observable variables for analysis to obtained the estimated Path Coefficient by using one SEM and there needs to be the basic assumption prior to the analysis that "the measurement value for analyzed are free of errors". These are considered to be the weak points of the classical structural equation model analysis. Therefore, the contemporary structure equation model analysis has included another model into the analysis, Measurement model. The measurement model is the factor analysis model which presents the relationships between observation variable and latent variables. Next assumed the common factor or latent variables for analyzed path coefficients assume. In the classical measurement model used the factor analysis for estimated Latent Variable. If the change to used Item response theory model (IRT Model) for estimate true ability score (è) and used the value of latent variables can be done based on the same principle. However, the only difference was the technique for latent variable estimation. Therefore, it could be concluded that Item Response Theory can be used with structural equation model analysis.

All standard errors of estimated path coefficients of the SEDPIRT model were smaller than those in PAL model at the .01 level of significant. This findings showed that the SEDPIRT analysis technique was superior than the PAL analysis technique in term of estimating the path coefficients of structural equation modeling. This may be explained the procedure for estimate latent variables was in item response theory was more Appropriate and consistent with the distribution of the data Than the measurement from confirmatory factor analysis model. This is because the IRT measurement model uses mathematical functions such as Logistic function in estimating the latent variables. Logistic function is used to explain the relationship between the probability of exam item responses or Each instrument has been exposed to the capabilities and features of the test as measured by the test version. This is consistent with the measure used in this research. And on the relationship of such to Item Characteristic Curve (ICC). There are many different types of ICC, depends on the model or casual model explain the per se relationships. The models that are often used included One - Parameter Model, Two - Parameter Model and Three - Parameter Model. When the model fit well with the data, it will result in invariance of Item parameter and Ability parameter (Kanjanawasri, 2007, pp.45-46) but factor analysis model is linear relationship between observation variable or the response scale for each factor or latent variable. Measurement model is consisted of a set of observable independent variables and observable dependent variables. The variable set X and Y are used for factor analyze which common factor (latent variables) and unique factor (error) (Wirutchai, 1999, pp.150-156) However, the data used in this research was the simulation data of the attribute measurements (Trait Variable) by tests in which 1 or 0 marks were given to each of the answers, and the rating scale of 5, 4, 3, 2, 1 scores was used to determine the weight of each of the responses. The factor analysis was used to estimate the relationship between the latent variables may post questions, each latent variable was not a linear relationship or a linear relationship at low levels. (Bollen, 1989, p.122) this result was consistent with the model (fit) with low levels too.

The SEDPIRT analysis yields a model with greater validity than the PAL at the .01 level of significance. The SEDPIRT analysis model shows a model validation of 97.50 % while the PAL one shows 77.50% that consistent with the findings in the past which SEDPIRT method was more effective than PAL in the estimated path coefficient in structural equation model, the standard error of estimation path analysis SEDPIRT was lower than PAL.

The iteration of P_{ij} by SEDPIRT analysis is significantly less than the PAL at the .01 level of significance which SEDPIRT method was more effective than PAL in the consistency for estimated path coefficient that the parameters was converge in the computer had iteration less and SEDPIRT was more the standard error of estimation path analysis and model validation than PAL.

All path coefficients (P_{ij}) of the SEDPIRT and PAL are positively correlated at the .01 level of significance. This result no consistent with the findings of Prajanban (2006, p.182) to modification of dichotomous item response theory in path analysis for latent variables model was found the mostly path coefficients (P_{ij}) of the SEDPIRT and PAL are not correlated at the .01 level of significance. However, considering the other aspects of the analysis. In the structural equation model analysis, the two methods used to measure the response of the sample was the same. However, there are just different ways to analyze the measurement model only. Path coefficient analysis is likely to be relevant. The correlation coefficient is positive, indicating that the path coefficients for each of the corresponding results in the model analysis. When you add the path coefficients also increases in the same direction. If the value of the coefficient will decrease with the decrease in the same direction.

It was found from applying the two techniques to empirical data that standard error in the estimation of all the path coefficients, the root mean square residual of the deviation, the number of iteration and the adjustment count in an attempt to make the two models consistent with empirical data in the SEDPIRT are less than the PAL; the Goodness-of Fit Index (GFI) and the Adjusted Goodness-of Fit Index with empirical data in the SEDPIRT are more than the PAL; and path coefficients of the SEDPIRT and PAL show a positive correlation at the .01 level of significance. The findings of the structural equation modeling analysis (SEDPIRT) compared to the PAL model with empirical data are consistent with the above analysis using simulated data. Shows analysis model, structural equation model SEDPIRT a new method that can be used for research on modeling structural equation with variables using measured with a rate 0 to 1 and the nature of the scale in the same model.

CONCLUSIONS

This study tested the structural equation model analysis technique, SEDPIRT which using true ability scores from Item Response Theory as observation variables and assumed that these observation variables did not have measurement errors. The SEDPIRT measurement is valid and wouldn't deviate because of changes in the tests or test takers. As well as had analyzed the model to estimated P_{ij} and check validity of the model by considering Chi-square value (χ^2), Goodness of Fit Indices, Root Mean Squared Residual, and P-value

The findings suggested that structural equation model analysis using SEDPIRT technique was more effective and consistency when estimating path coefficients than the PAL technique. The results from the analysis further supported that standard errors of estimated path coefficients from the SEDPIRT technique were smaller and the iteration numbers were lesser than the PAL model, which resulted in the SEDPIRT analysis yields a model with greater validity than the PAL. In addition, path coefficients of the SEDPIRT and PAL show a positive correlation that path increased or decrease in the same direction by this it showed that both analysis methods resulted in the same analysis result. This research suggested the alternative way of structural equation model analysis which credibility of direct and indirect effect in the structural equation model was more accurate.

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