CHAPTER 7

ANALYZING THE MODERATING VARIABLE IN A MODEL

Researches in business, social sciences and other disciplines involve theories concerning moderating variables. Thus, researchers in these areas should know how to model the moderators and analyse them in their work.

Moderating variable is the variable that "moderates the effects" of an independent variable on its dependent variable. The social science researchers, in particular, define moderator as the variable that "interfere" in the relationship between an independent variable and its corresponding dependent variable. For illustration, let M be the moderator variable in the X-Y relationship. Then the moderation role of M is "to alter" the effects of X on Y.

Before introducing a moderator into the model, the effects of independent variable X on its dependent variable Y must exist and significant. Thus, when a moderator M enters the model, the causal effects would change due to some "interaction effect" between independent variable X and moderator variable M just entered. As a result, the "effects" of X on Y could either increase or decrease. In other words, the effect of independent variable on its dependent variable would depend on the level of moderator variable.

7.1 THE SCHEMATIC DIAGRAM FOR MODERATING VARIABLE IN A MODEL

Example 1:

Let X = the amount of environmental news in the media educating the public concerning the safe and clean environment. The campaign intends to make the public aware of environmental degradation and that they should help the environment by switching to environmental friendly products. Let Y = the respondents' intention to purchase green products, and let M = their level of education as a moderator. If the effect of environmental campaign (X) in influencing the public to purchase green products (Y) is more visible among higher educated consumers compared to lower educated consumers, then we can say that education (M) is the variable that moderates the relationship between **Environmental Awareness Campaign** and **Intention to Purchase Green Products** by the public.

Figure 1 illustrates the position of moderating variable M in the in the X-Y relationship.

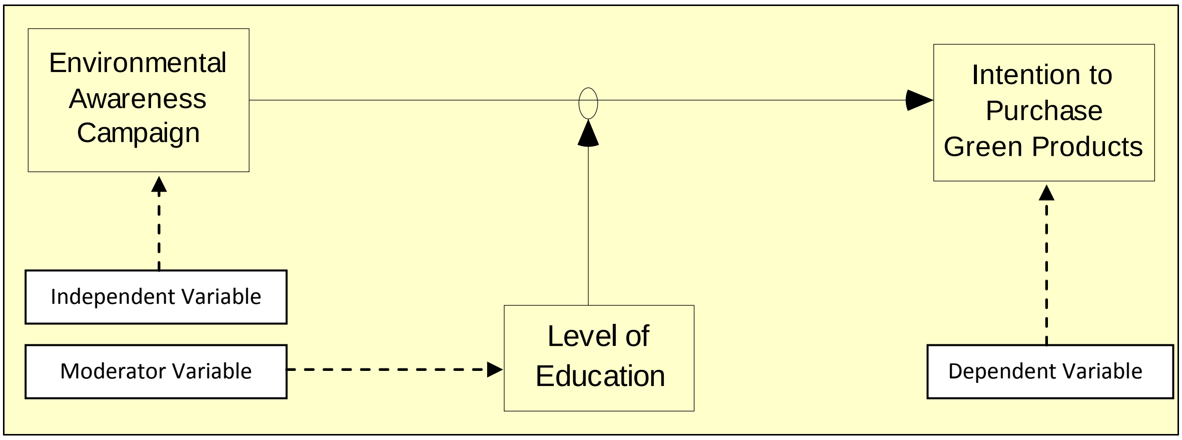

Figure 1: The schematic diagram showing the independent variable, dependent variable and a moderator in a model

Example 2:

Let X = monetary incentives, Y = work motivation, and M = age of workers. If the effects of monetary incentives (X) on work motivation (Y) are more visible on certain age groups (M), then one could claim that age of workers (M) moderates the relationship between monetary incentives (X) and their work motivation (Y). Figure 2 illustrates the position of variable M in the X-Y relationship.

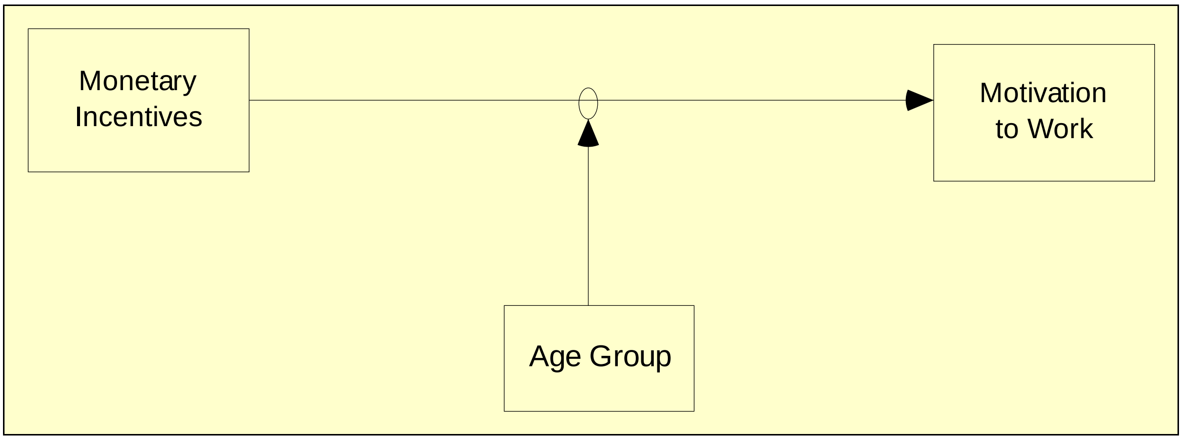

Figure 2: The representation of Age as moderating variable in the relationship between Monetary Incentives and Work Motivation

Example 3:

Let X = the corporate reputation of manufacturers, Y = customers' brand loyalty, and M = the customers' socio-economic status. If the effects of manufacturer's corporate reputation (X) on customers' brand loyalty (Y) are depending on their level of socioeconomic status (M), then one could claim that respondents' socioeconomic status moderates the effects of the firm's corporate reputation (X) on consumers' brand loyalty (Y). Figure 3 illustrates the position of socioeconomic status (M) in the corporate reputation and brand loyalty relationship.

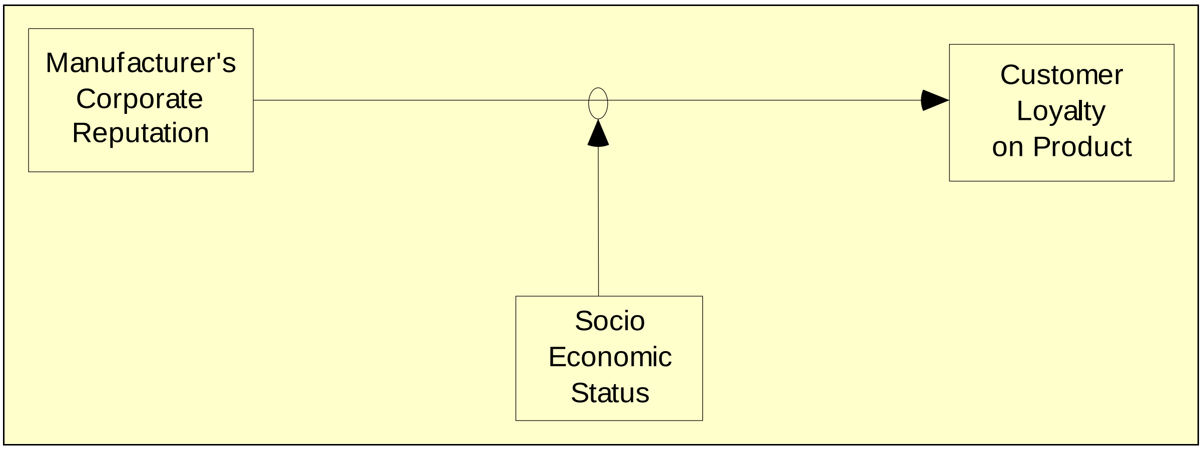

Figure 3: The representation of Socio-Economic Status as moderating variable in the Corporate Reputation – Brand Loyalty relationship

7.2 MODELING THE INTERACTION EFFECTS OF A MODERATOR FOR THE OBSERVED VARIABLE

As has been said earlier, although moderation implies a weakening of a causal effect, a moderator can also enhance the causal effect. Remember: The term interaction and moderation carries the same meaning. The interaction between independent variable and moderator in the model could decrease or increase the effects on dependent variable.

A key part of moderation is the measurement of causal effect of independent variable X on dependent variable Y for different level of moderator variable M. In statistics, the effect of X on Y for a fixed value of M is referred as the "simple effect" of independent variable on its dependent variable. Let X is an independent variable and Y is a dependent variable. The simple regression equation will be:

$$\mathbf{Y = \beta_0 + \beta_1 X + e}$$

Let assume that the above regression relation does exists and statistically significant. When the moderator variable M enters the model, the moderation effect of M is modeled in the regression equation as follows:

$$\mathbf{Y = \beta_0 + \beta_1 X + \beta_2 M + \beta_3 XM + e}$$

The regression coefficient β_3 measures the **interaction effect** between independent variable X and moderating variable M. Note that the regression coefficient β_1 measures the simple effects of X when the value of M = 0 (no interaction effects involved). Then, the test of moderation is operationalized by the product term XM (the multiplication between independent variable X and moderator variable M).

In order to test the moderation in a model, one needs to test β_3 (the coefficient of interaction term XM). If β_3 is significant, then one could conclude that moderator variable M moderates the relationship between X and Y.

Testing moderator for observed variables

Testing moderation for observed variables involve the Ordinary Least Squares (OLS) regression in which the dependent variable, Y, is regressed on the interaction term XM and the main effects X and M. If both variables X and M are continuous, the researcher needs to create the mean-centred value for X and M where X_i' = (X_i – mean of X) and M_i' = (M_i – mean of M). Thus, the new variable X and M has a mean of zero. Now XM = (X_i') * (M_i'). Variable Y does not have to be cantered.

7.3 SCALE OF MEASUREMENT FOR A MODERATING VARIABLE

The researcher should employ the interval or ratio scale for measuring both independent and dependent variables since the analysis involves parametric methods. As for the moderator variable, it can be measured using any scale (nominal, ordinal, interval, and ratio). Among the popularly used moderating variables in research are the respondent's demographic characteristics (nominal) and the level of treatment variable applied (ordinal).

Both the Ordinary Least Square regression (OLS) and Structural Equation Modeling (SEM) could be employed if the dependent variable (Y) is measured using the interval or ratio scale. However, if the dependent variable is measured using a dichotomous scale (outcome is either yes or no), then the logistic regression should be employed.

7.4 MODELING THE MODERATING EFFECTS FOR OBSERVED VARIABLES

Having all variables and data in hand, the next thing the researcher needs to know is how to analyze the moderator and prove that M is actually moderating the relationship between X and Y. In addition to the variable X, M, and Y, the researcher needs to create a new variable namely XM from the product of X multiply M. Thus, the variables involve will be X, Y, M, and XM. The information can be modeled in the following regression equation:

$$\mathbf{Y} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}X + \boldsymbol{\beta_2}M + \boldsymbol{\beta_3}XM + \mathbf{e_1}$$

Figure 4 illustrates how the regression equation is modeled in AMOS graphic.

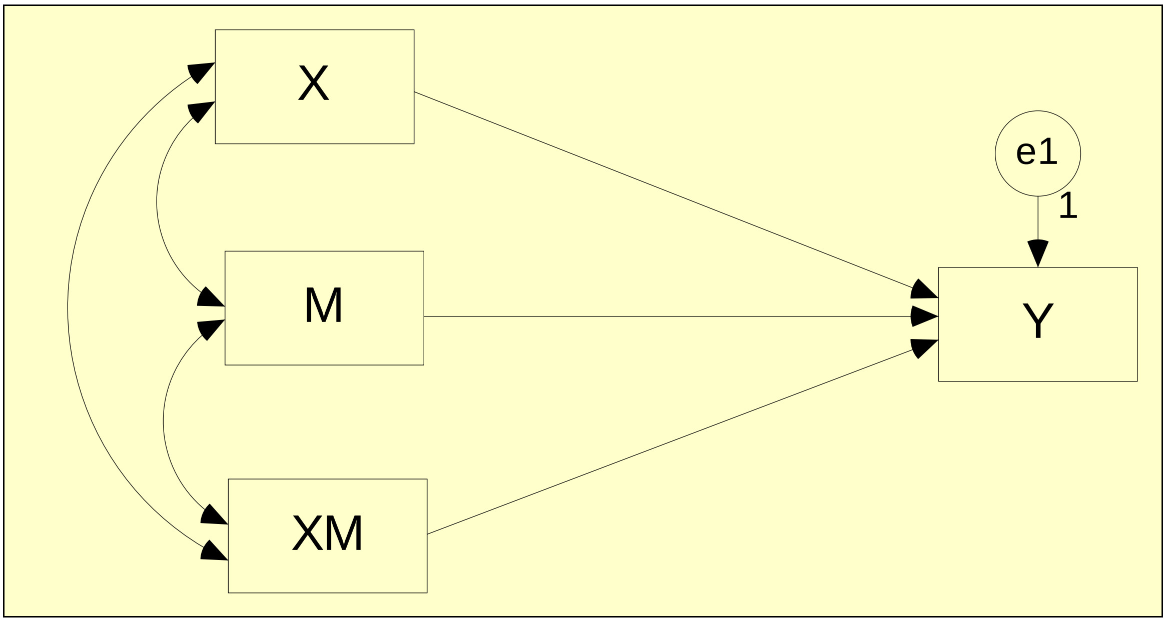

Figure 4: The modelling of moderating variable M in AMOS for observed variables

As shown in Figure 4, three hypotheses testing for path analysis is required namely:

1. The X-Y relationship (testing for $\boldsymbol{\beta_1}$) – we indicate as Hypothesis 1
2. The M-Y relationship (testing for $\boldsymbol{\beta_2}$) – we indicate as Hypothesis 2
3. The XM-Y relationship (testing for $\boldsymbol{\beta_3}$) – we indicate as Hypothesis 3

The moderation effects of moderator variable M in the model occurs if Hypothesis 3 ($\boldsymbol{\beta_3}$) is significant and Hypothesis 2 ($\boldsymbol{\beta_2}$)is not significant. As for Hypothesis 1 ($\boldsymbol{\beta_1}$), there are two possibilities that could occur:

1. If Hypothesis 1 is **not significant** – then the "complete moderation" occurs
2. If Hypothesis 1 is **significant** – then the "partial moderation" occurs.

7.5 ANALYZING THE MODERATING EFFECTS FOR OBSERVED VARIABLES

We shall go through some practical examples in order to enhance our understanding concerning the concept of moderation.

Suppose the researcher is interested to assess the moderation effects of age of workers (M) in the relationship between the monetary incentives given to them (X) and their monthly productivity

(Y). The AMOS model illustrating the researcher's theoretical argument is given in Figure 5. All variables in the model are directly observed, thus the rectangles are employed instead of ellipses.

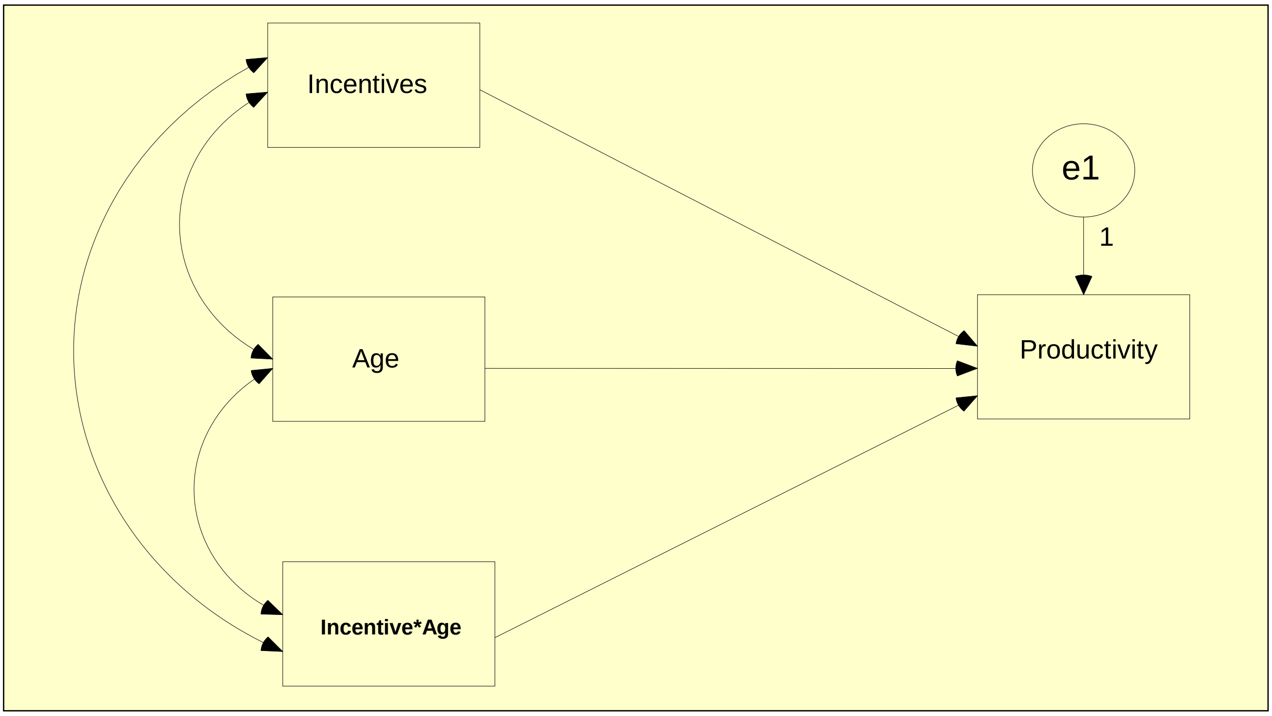

Figure 5: The model in AMOS Graphic for testing Age as Moderator

The measurement of variables involved in the model.

Independent variable = Monetary Incentives (can be interval or ratio scale)

Dependent variable = Monthly Productivity (can be interval or ratio scale)

Moderating variable = Age of workers (can be interval or ratio scale)

The corresponding AMOS output for the above model where all variables involved are interval or ratio is given in Figure 6

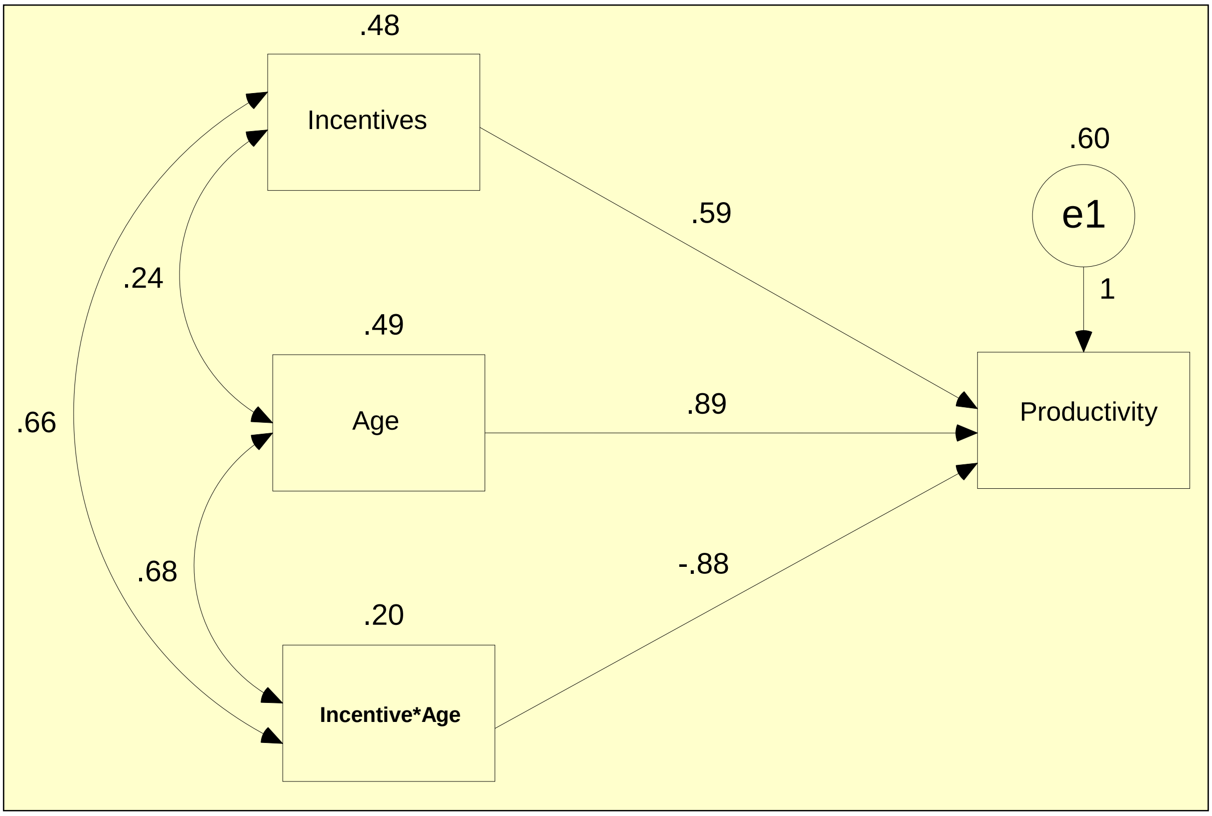

Figure 6: The AMOS output showing the regression coefficients, variance, and covariance

The hypotheses testing required in analyzing a moderator in Figure 6

Hypothesis 1: The Monetary Incentives given to workers has significant effects on their monthly productivity

Table 1: Testing the causal effects of Incentives on Productivity

			Estimate	S.E.	C.R.	P	Result
Productivity	<---	**Incentives**	0.59	0.068	8.636	**0.001**	**Significant**

In this case, **Hypothesis 1:** the hypothesis that the causal effects of incentives on productivity are significant **is supported**.

Hypothesis 2: The Workers' age level has significant effects on their productivity

Table 2: Testing the causal effects of Age on Productivity

			Estimate	S.E.	C.R.	P	Result
Productivity	<---	**Age**	0.89	0.61	1.451	**0.072**	**Not Significant**

In this case, the hypothesis that the effects of age on productivity are significant is **not supported**.

Hypothesis 3: The workers' age moderates the relationship between incentives and productivity

Table 3: Testing the Moderating Effects of Incentives*Age on Productivity

			Estimate	S.E.	C.R.	P	Result
Productivity		Incentive*Age	-0.88	0.186	-4.742	**0.001**	**Significant**

In this case, the hypothesis that the moderating effects of workers' age (M) on relationship between incentives (X) and their productivity (Y) are significant **is supported**.

The type of moderation that occurs in this case is partial moderation since the hypothesis for the main effect is still significant after the moderator enters the model.

Note: The regression coefficient of product term (incentive*age) on productivity is negative, which indicates that the moderating variable (age) weakens the causal effects of monetary incentives (X) on monthly productivity (Y). In other words, the increase in workers age would give negative effects on the firm's productivity.

7.6 MODELING THE MODERATING EFFECTS FOR LATENT CONSTRUCTS

Analyzing the moderating effects for the model with latent constructs is very complicated. The normal modeling procedure using interaction terms is not practical with latent constructs since it would cause problems with model convergence as well as distortion of standard errors. In the end, it resulted in **model misfit** and the procedure stops.

Figure 7 illustrates how the moderator is modeled when analyzing the model consisting latent constructs.

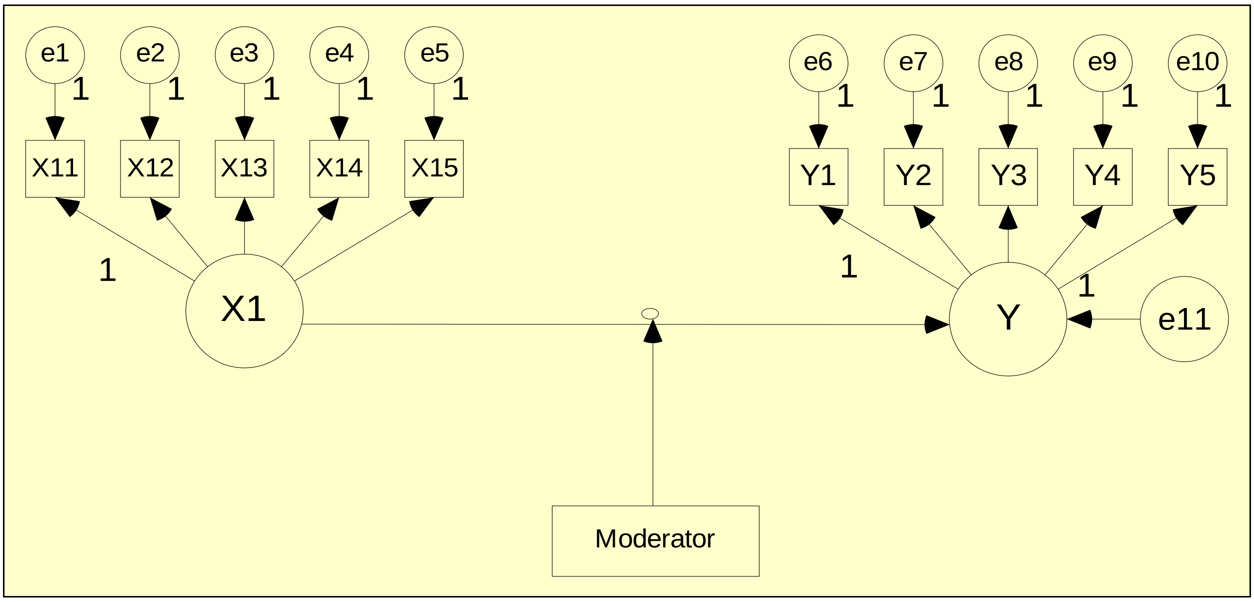

Figure 7: Modeling the moderator variable in the path between X_1 and Y

Alternatively, the Multi-Group CFA has been suggested as an alternative method for assessing the effect of moderator variable in the model. The researcher only needs to identify the path of interest where the moderator variable is to be assessed. This particular path would be constrained with parameter = 1 and the model is termed as the constrained model. The procedure will estimate two models separately. One is the **constrained model** while the other one is the **unconstrained model**. The step by step process for Multi-Group CFA is discussed.

7.7 ANALYZING THE MODERATOR FOR LATENT CONSTRUCTS: THE MULTI-GROUP CFA

There are few steps involved in performing Multi-Group CFA:

1) Split data into two groups based on the **moderator variable** to be tested.
2) Save data into two separate files: Name the files as dataset 1 and dataset 2.
3) **Select the path of interest** in the model to test the moderator variable.
4) Develop two separate AMOS models: Rename as model 1 and model 2.
5) In Model 1, constraint the parameter in the path of interest to be equal to 1.
6) Name model 1 as the **constrained model**.
7) In model 2, do not constrain the relationship in the path of interest.
8) Name model 2 as the **unconstrained model.**
9) Use dataset 1: Estimate the constrained model
10) Use the same dataset 1: Estimate the unconstrained model
11) Obtain the difference in Chi-Square value between the constrained and the unconstrained model. If the value differs by more than **3.84**, then the moderation occurs in that path.
12) Repeat the same procedure using dataset 2.
13) Use dataset 2: Estimate the constrained model
14) Use the same dataset 2: Estimate the unconstrained model
15) Obtain the difference in Chi-Square value between the constrained and the unconstrained model. If the value differs by more than 3.84, then the moderation occurs in that path.

Example: Suppose we are modeling the effect of X_1 and X_2 on Y (Figure 8). One of the objectives for this research is to examine the moderation effect of a variable namely education in the relationship path between X_1 and Y.

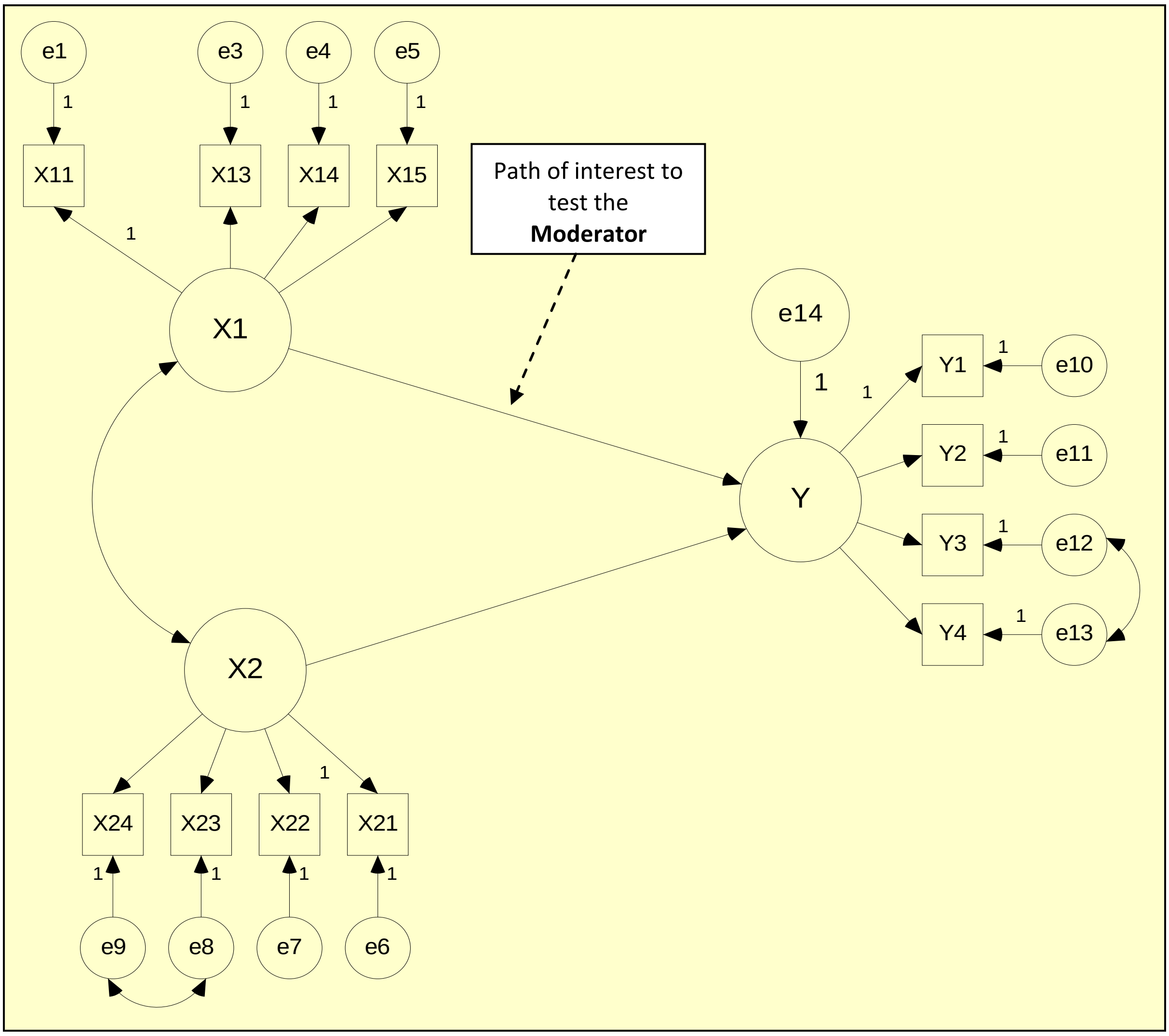

Figure 8: The path where the moderator Education is to be examined.

The path of interest where the moderation tests is to be carried out is shown in Figure 8. First of all, the data is sorted in ascending order based on respondents' level of education. Then the data is split and save into two separate data files. Data 1 is renamed as **low education** group, while data 2 is renamed as **high education** group.

Secondly, put a parameter constraint on the selected path to be equal to "1" as shown in Figure 9. This model is renamed as the **constrained model**.

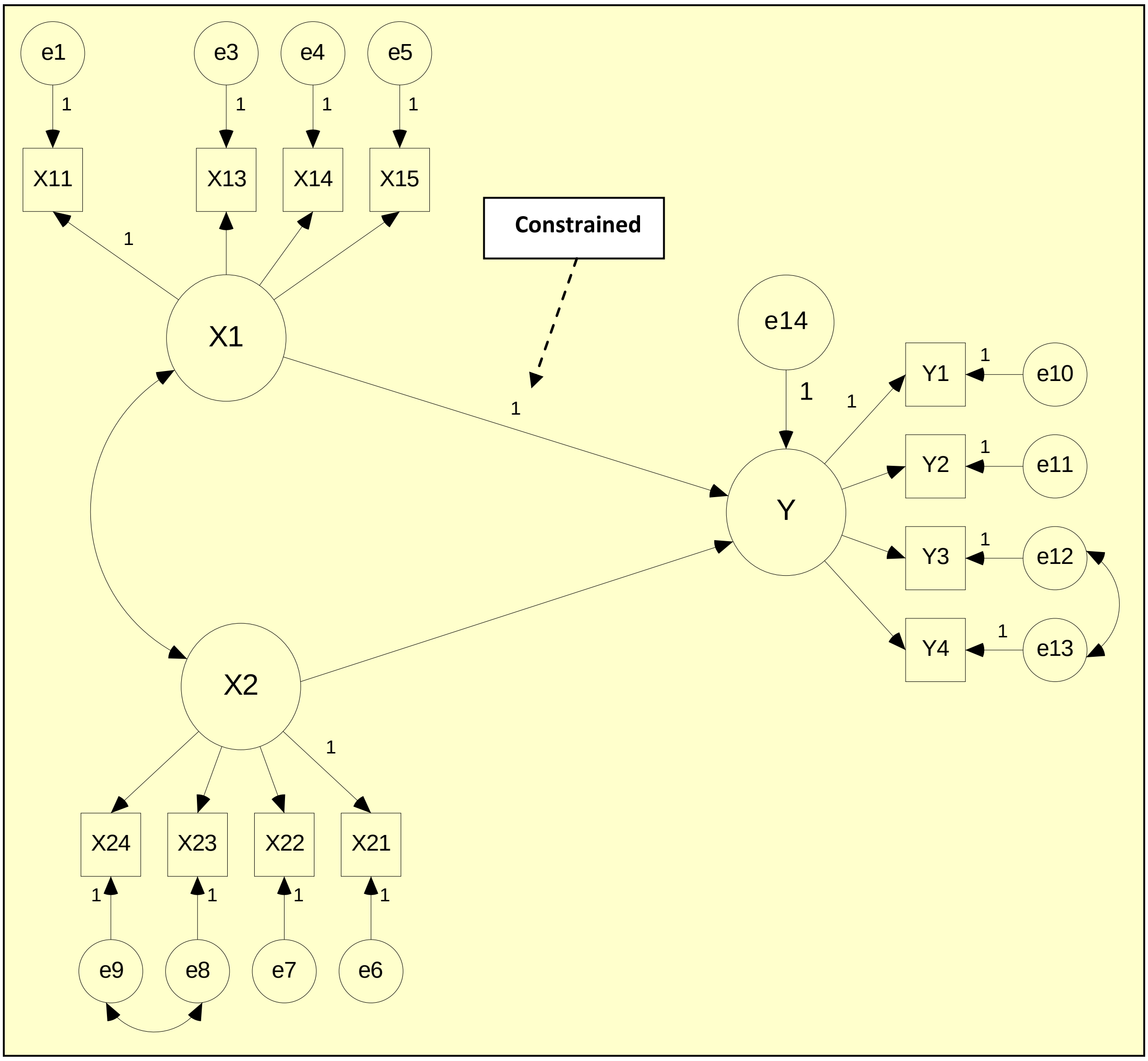

Figure 9: The Constrained Model: The parameter in the path of interest (X_1 to Y) is constrained to 1.

Thirdly, using the same model, remove the parameter constraint in the path as shown in Figure 10. This model is renamed as the **unconstrained model**. Now the researcher has two models to be assessed namely the constrained and the unconstrained model.

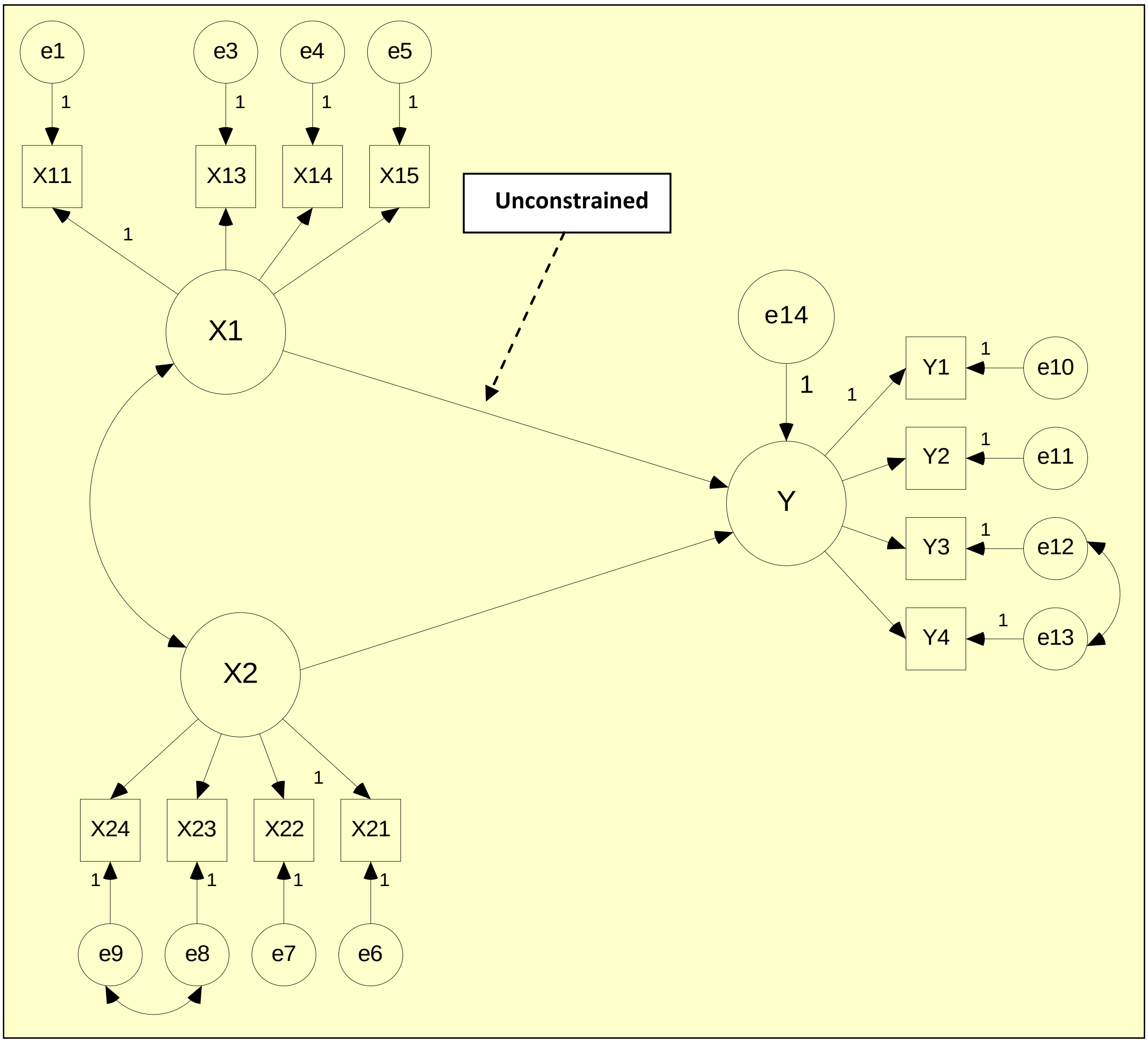

Figure 10: The Unconstrained Model: The coefficient in the path (X_1 to Y) is not constrained.

Next, obtain the estimate for both the constrained model and also the unconstrained model using the first dataset (low education group). The output is presented in Figure 11 for the constrained model and in Figure 12 for the unconstrained model.

The procedure for testing moderation is carried out as shown in Table 1a.

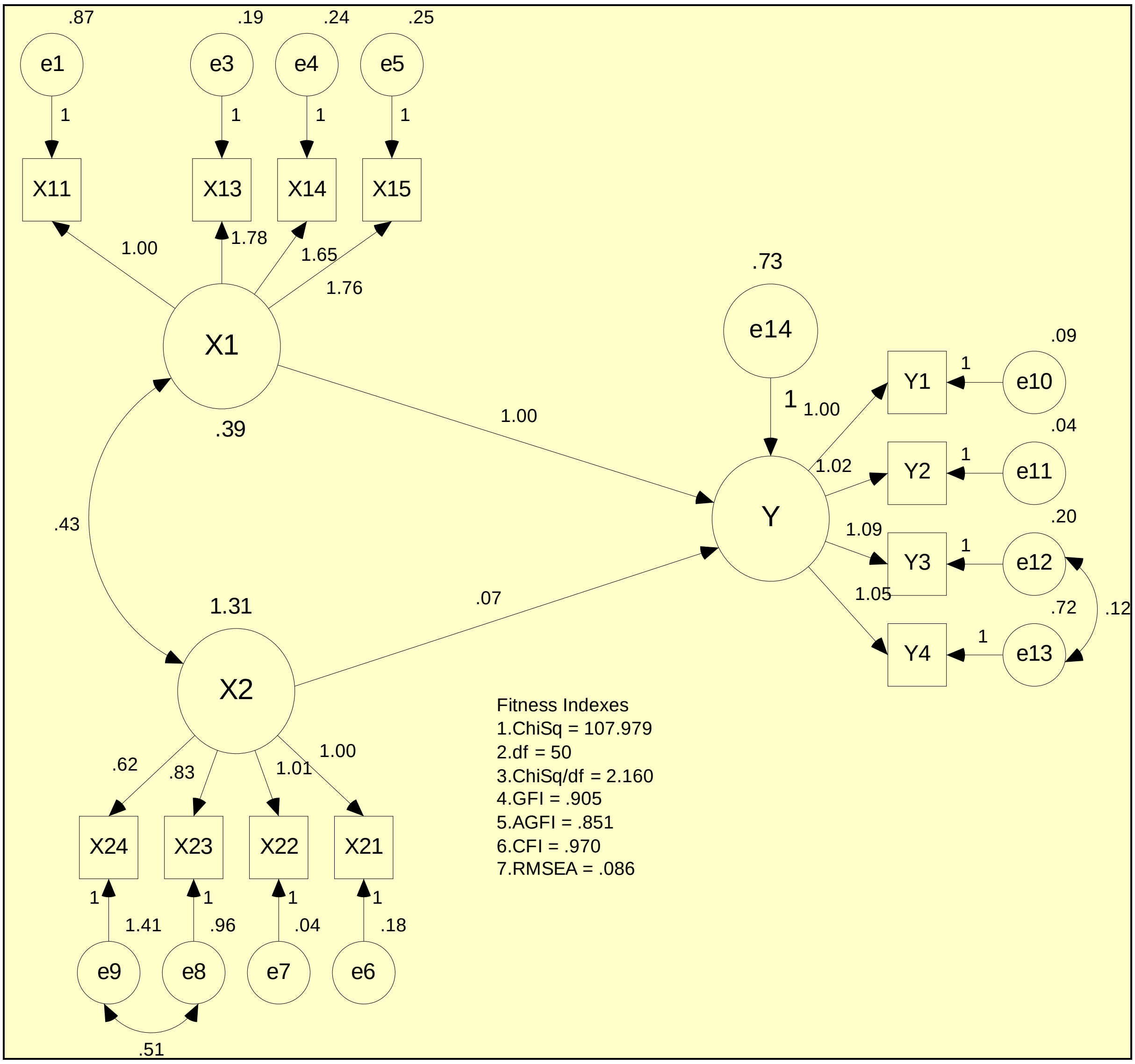

Figure 11: Low Education Group: The output for the constrained model.

The Chi-Square Value and DF for the constrained model

Model	NPAR	**CMIN**	**DF**	P	CMIN/DF
Default model	28	**107.979**	**50**	0.000	2.160
Saturated model	78	0.000	0		
Independence model	12	2000.617	66	0.000	30.312

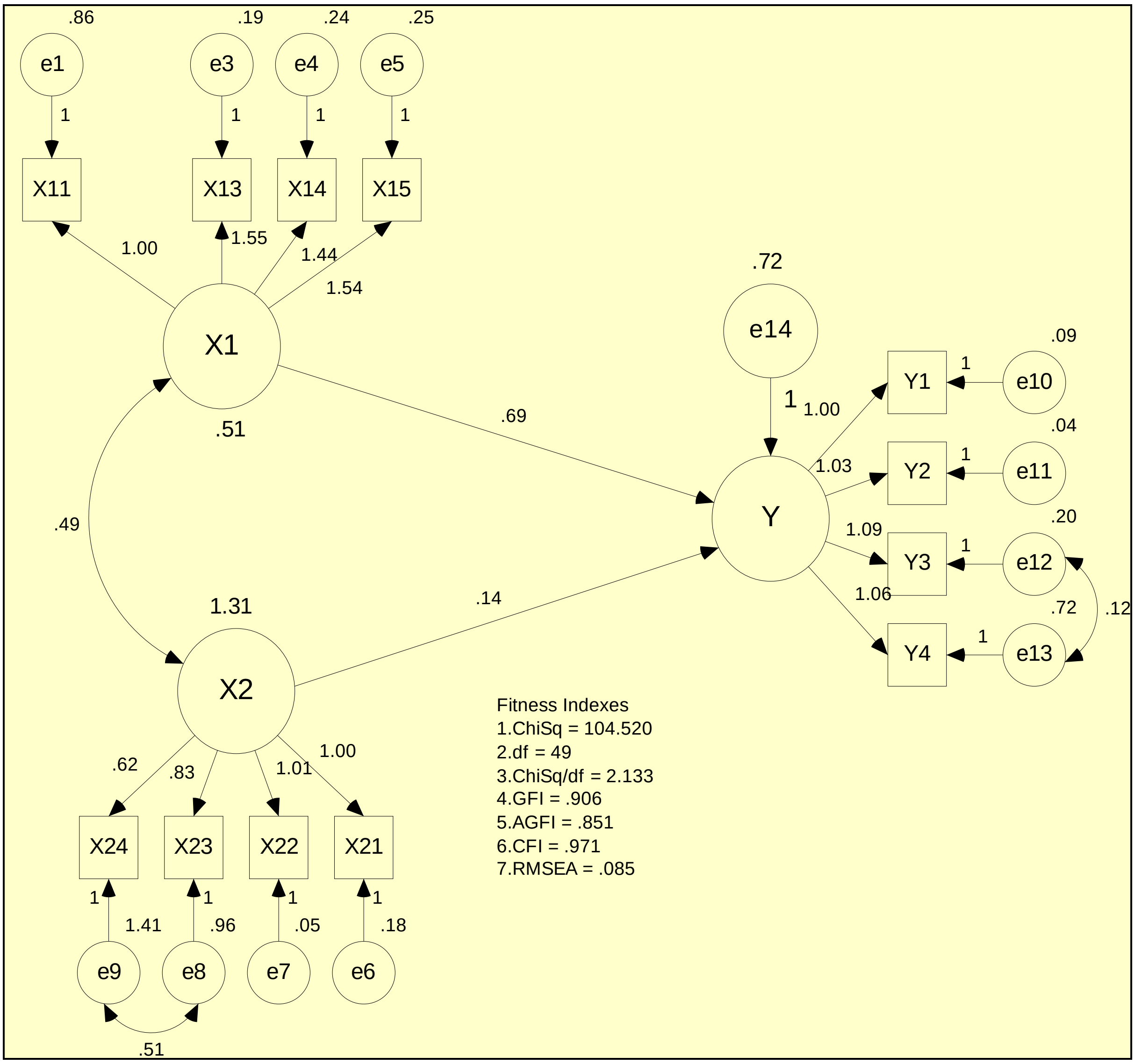

Figure 12: Low Education Group: The output of the unconstrained model.

The Chi-Square Value and DF for the unconstrained model

Model	NPAR	**CMIN**	**DF**	P	CMIN/DF
Default model	29	**104.520**	**49**	0.000	2.133
Saturated model	78	0.000	0		
Independence model	12	2000.617	66	0.000	30.312

Table 1a: The Moderation Test for Low Education group data

	Constrained Model	Unconstrained Model	Chi-Square Difference	Result on Moderation	Result on Hypothesis
Chi-Square	**107.979**	**104.520**	**3.459**	Not Significant	Not Supported
DF	**50**	**49**	**1**		
GFI	0.905	0.906			
AGFI	0.851	0.851			
CFI	0.970	0.971			
RMSEA	0.086	0.085			
CMIN/DF	2.160	2.133			
The hypothesis statement: Ha: Respondent's education moderates the relationship between X_1 and Y					Not Supported

*******The moderation test is not significant since the difference in Chi-Square value between the constrained and unconstrained model is less than 3.84.

The difference in Chi-Square value is 3.459 (107.979 - 104.520), while the difference in Degrees of Freedom is 50 – 49 = 1. For the test to be significant, the difference in Chi-Square value must be higher than the value of Chi-Square with 1 degree of Freedom, which is 3.84

The procedure for performing the test of moderation for the same variable (education) using another dataset (high education group) is carried out in Table 1b. The test of hypothesis should the produce the same result.

If the result differs, then go back to the original data and redefine the levels of education. Regroup the data based on the new definition for low education level and high education level. Repeat the same procedure again.

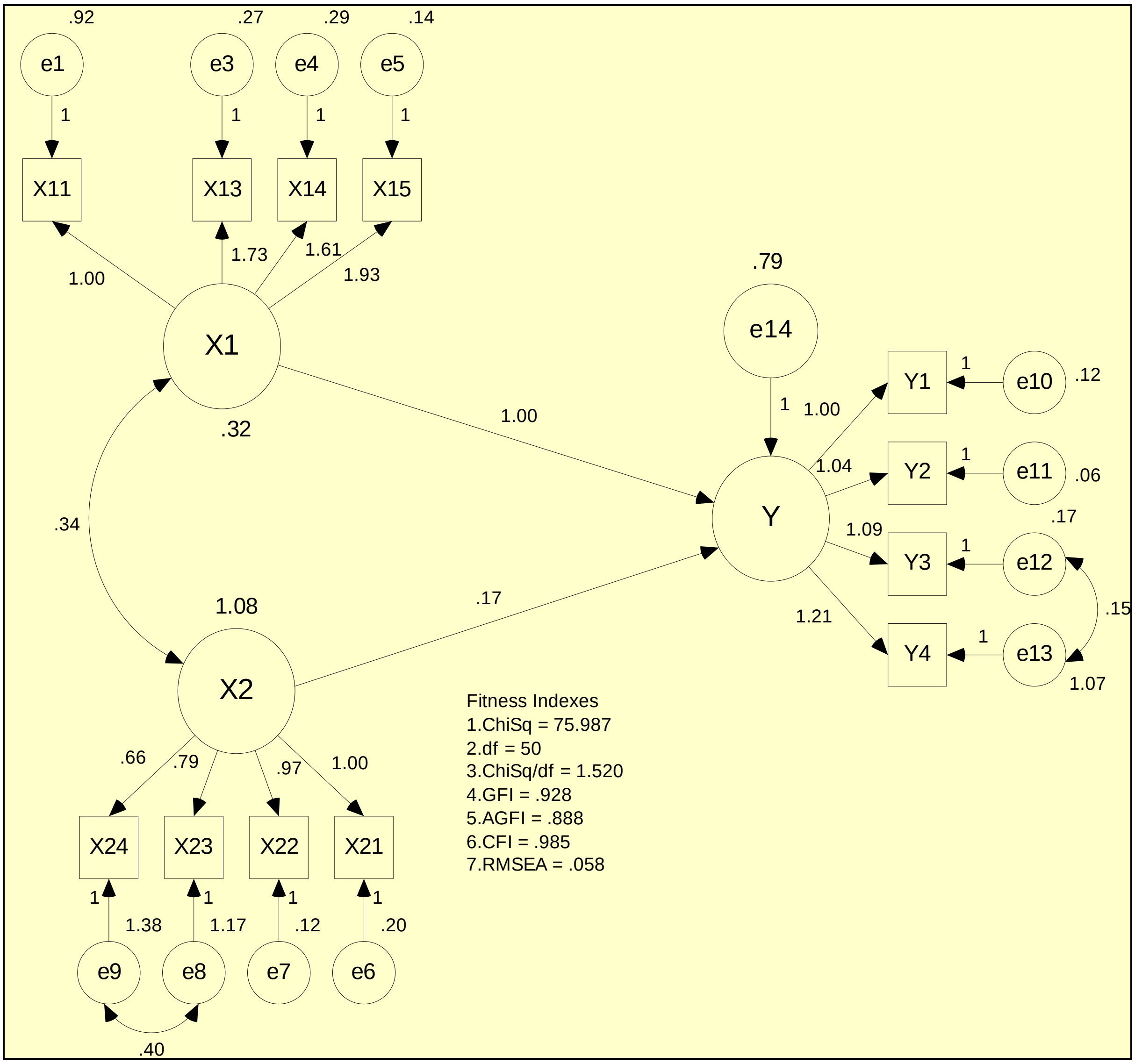

Figure 13: High Education Group: The output for the constrained model.

The Chi-Square value and DF for the constrained model

Model	NPAR	**CMIN**	**DF**	P	CMIN/DF
Default model	28	**75.987**	**50**	0.010	1.520
Saturated model	78	0.000	0		
Independence model	12	1760.721	66	0.000	26.678

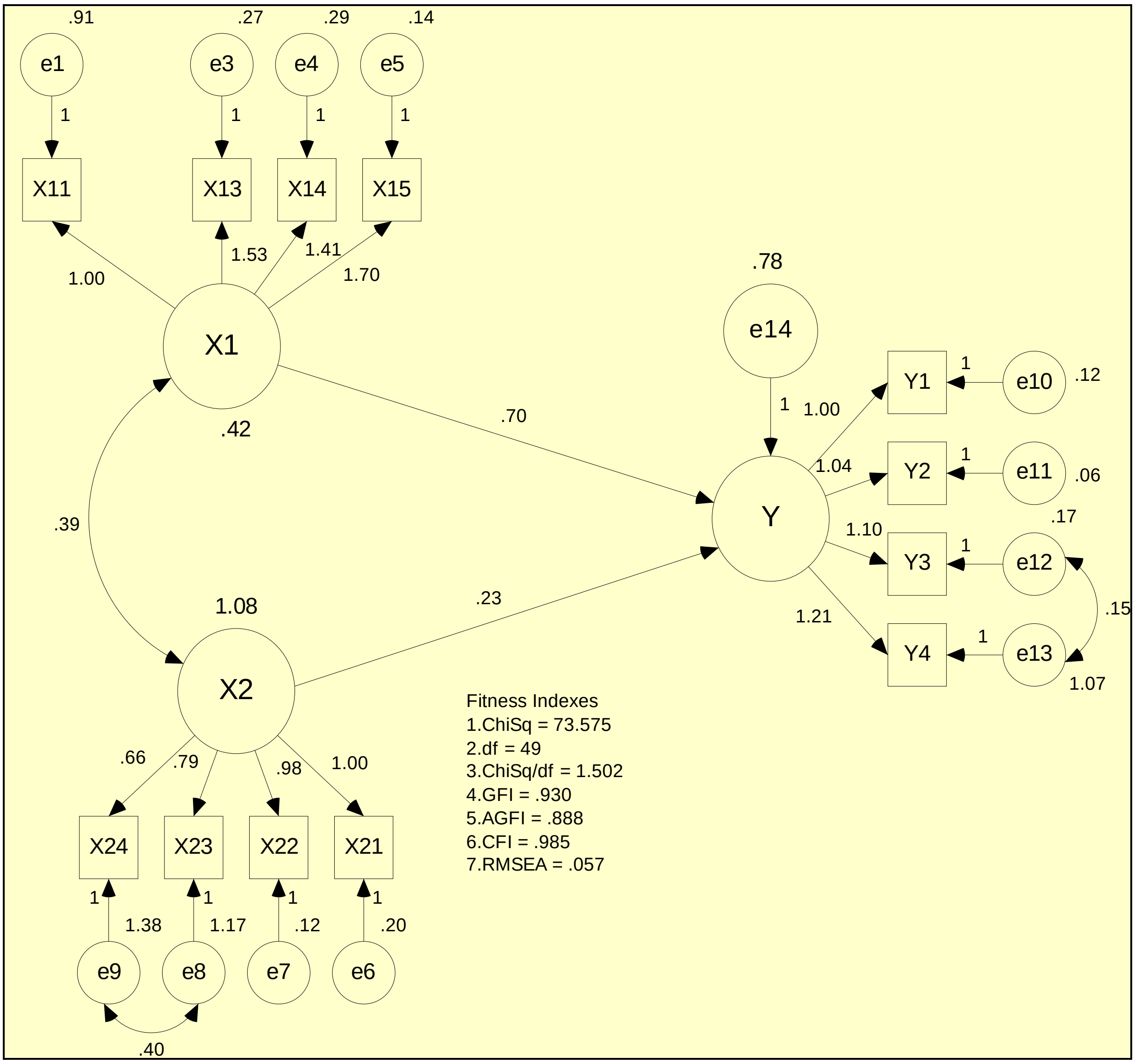

Figure 14: High Education Group: The output for the unconstrained model.

The Chi-Square Value and DF for the unconstrained model

Model	NPAR	**CMIN**	**DF**	P	CMIN/DF
Default model	29	**73.575**	**49**	0.013	1.502
Saturated model	78	0.000	0		
Independence model	12	1760.721	66	0.000	26.678

Table 1b: The Moderation Test for High Education level

	Constrained Model	Unconstrained Model	Chi-Square Difference	Result on Moderation	Result on Hypothesis
Chi-Square	**75.987**	**73.575**	**2.412**	Not Significant	Not Supported
DF	**50**	**49**	**1**		
GFI	0.928	0.930			
AGFI	0.888	0.888			
CFI	0.985	0.985			
RMSEA	0.058	0.057			
Chisq/df	1.520	1.502			
The hypothesis statement: Ha: Respondent's education moderates the relationship between X_1 and Y					Not Supported

*******The moderation test is not significant since the difference in Chi-Square value between the constrained and unconstrained model is less than 3.84. The difference in Chi-Square value is 2.412 (75.987 - 73.575), while the difference in Degrees of Freedom is 50 – 49 = 1. For the test to be significant, the difference in Chi-Square value must be higher than the value of Chi-Square with 1 degree of Freedom, which is 3.84

The test of hypothesis for moderation that has been carried out found that the moderator variable "respondents' education" <u>does not moderate</u> the causal effects of X_1 on Y.

Suppose that the researcher has another objective - to determine whether the same moderator variable (respondents' education) moderates another causal path namely X_2 to Y. Now the selected path has changed to the new path (X_2 to Y). To test the moderation effect of respondents' education for the new path, the researcher needs to repeat the same procedure that has been explained earlier.

The analysis and moderation test for the new path is explained in the following example.

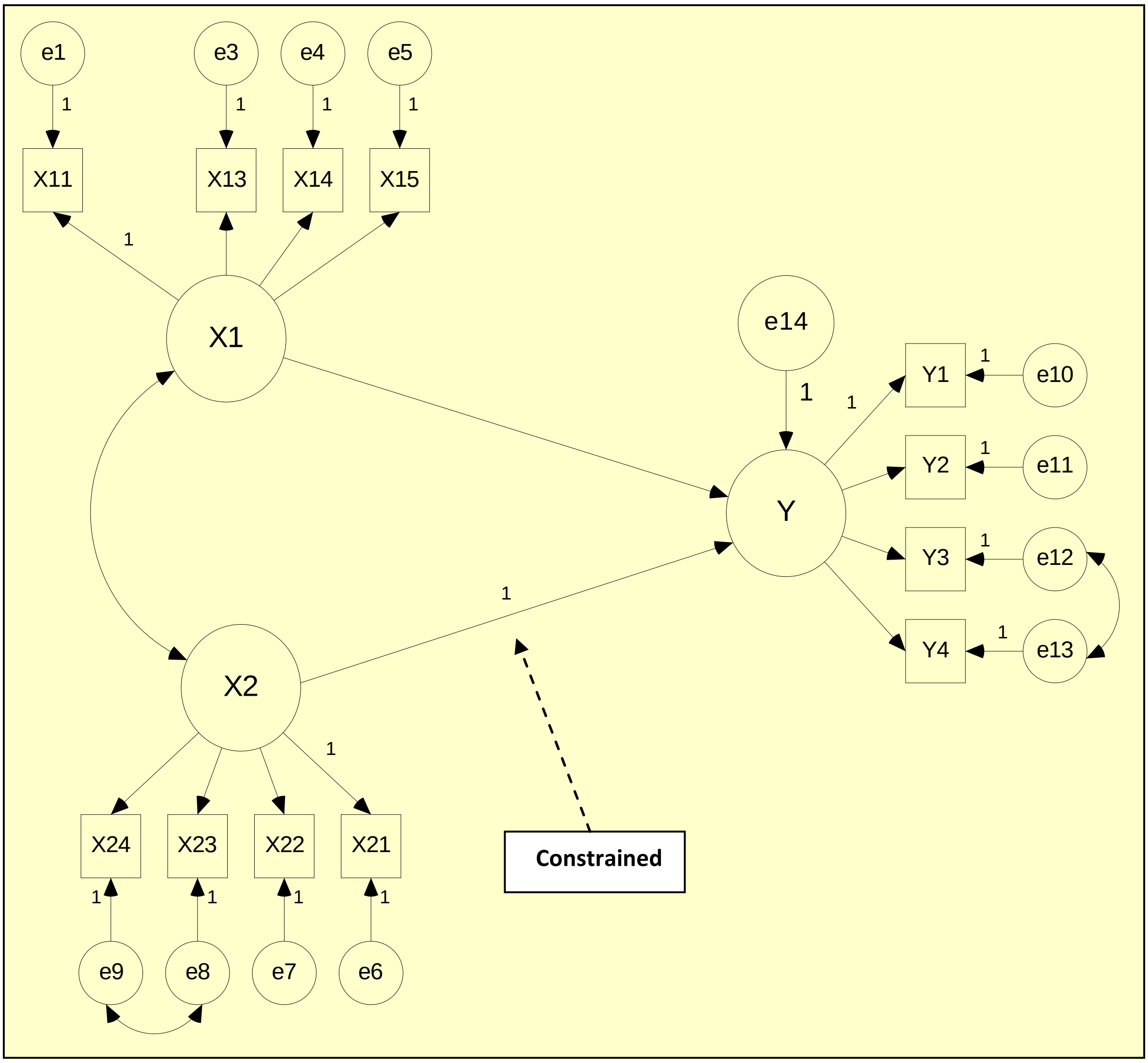

Figure 15: The Constrained Model: The parameter in the selected path (X_2 to Y) is constrained to 1.

Recall: The parameter constraint is fixed in the path where the moderation effect will be examined, and the data is split based on the moderator variable of interest.

In the above example, the path of interest is X_2 to Y and the moderator variable to be tested is respondents' education. Let's begin the analysis using the low education group.

The output for the constrained and unconstrained models is presented in Figure 16 and Figure 17 respectively. The test of moderation is carried out in Table 2a.

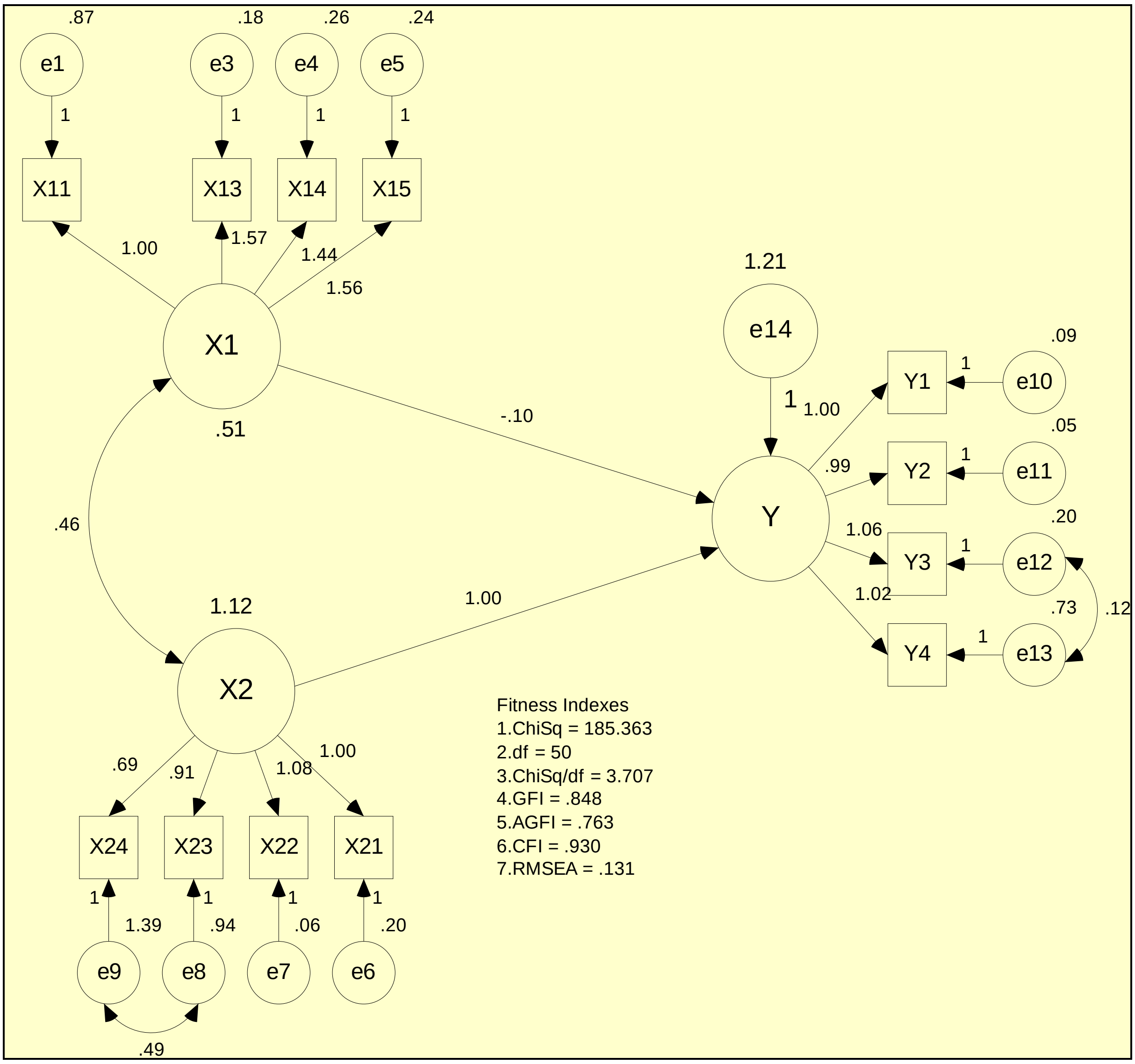

Figure 16: Low Education Group: The output for Constrained Model.

The Chi-Square value and DF for the constrained model

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	28	**185.363**	**50**	0.000	3.707
Saturated model	78	0.000	0		
Independence model	12	2000.617	66	0.000	30.312

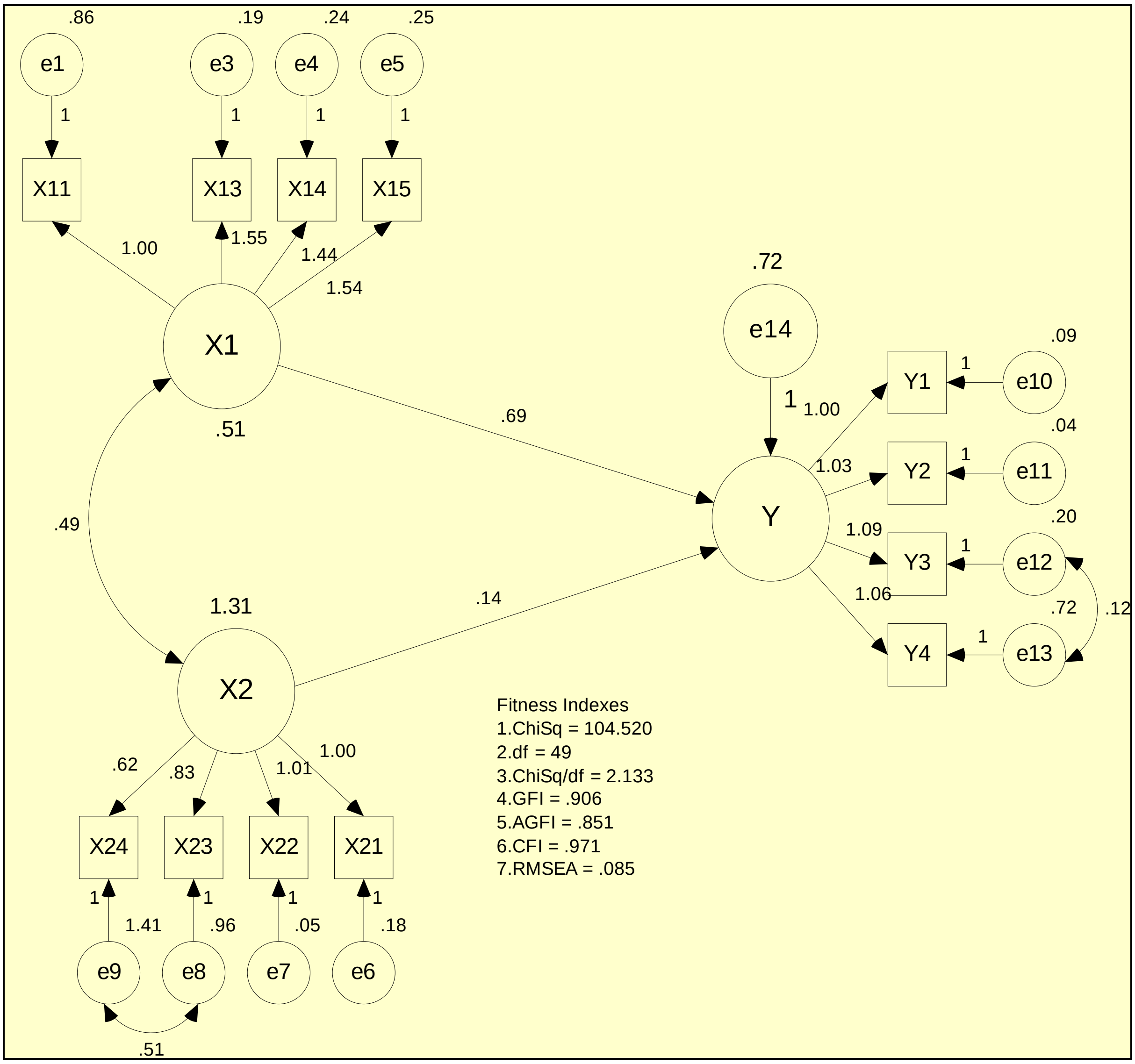

Figure 17: Low Education Group: The output for Unconstrained Model.

The Chi-Square Value and DF for the Unconstrained Model

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	29	**104.520**	**49**	0.000	2.133
Saturated model	78	0.000	0		
Independence model	12	2000.617	66	0.000	30.312

Table 2a: The Moderation Test for Low Education Group Data

	Constrained Model	Unconstrained Model	Chi-Square Difference	Result on Moderation	Result on Hypothesis
Chi-Square	**185.363**	**104.520**	**80.843**	Significant	Supported
DF	**50**	**49**	**1**		
GFI	0.848	0.906			
AGFI	0.763	0.857			
CFI	0.930	0.971			
RMSEA	0.131	0.085			
Chisq/df	3.707	2.133			
The hypothesis statement: Ha: Respondent's education moderates the relationship between X_2 and Y					Supported

*******The moderation is significant since the difference in Chi-Square value between the constrained and unconstrained model is more than 3.84. The difference in Chi-Square value is (185.363 – 104.520) = **80.843**, while the difference in Degrees of Freedom is 50 – 49 = 1. For the test to be significant, the difference in Chi-Square value must be higher than the value of Chi-Square with 1 degree of Freedom, which is 3.84

The test of hypothesis for moderation that has been carried out found that the moderator variable "respondents' education" does moderate the causal effects of X_2 on Y.

The procedure for performing the test of moderation for the same variable (education) using another data-set (data 2) is carried out in Table 2b. The test of hypothesis is expected to produce the same result that the respondents' level of education does moderate the causal effects of X_2 on Y.

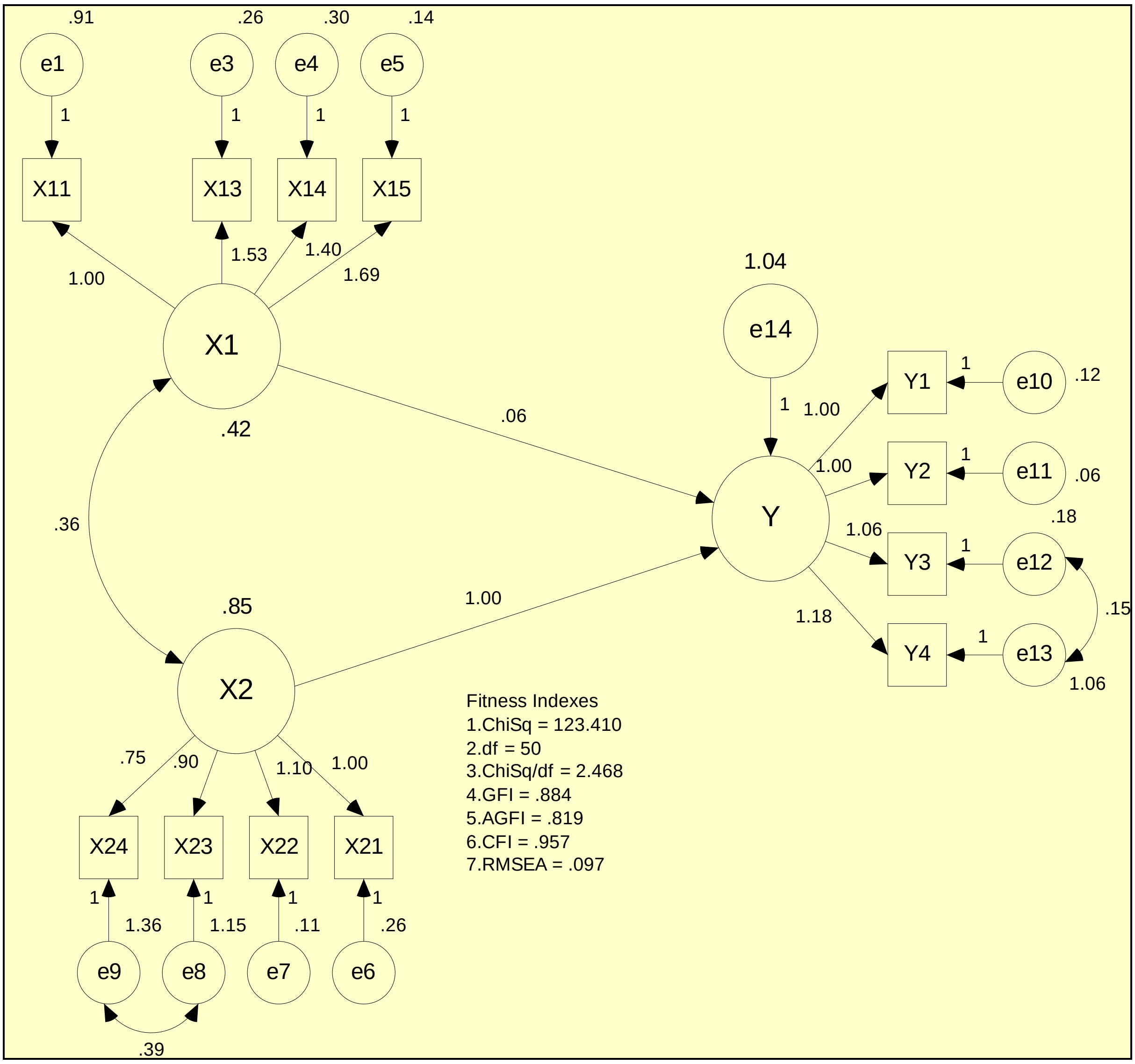

Figure 18: High Education Group: The output for Constrained Model.

The Chi-Square value and DF for the constrained model

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	28	**123.410**	**50**	0.000	2.468
Saturated model	78	0.000	0		
Independence model	12	1760.721	66	0.000	26.678

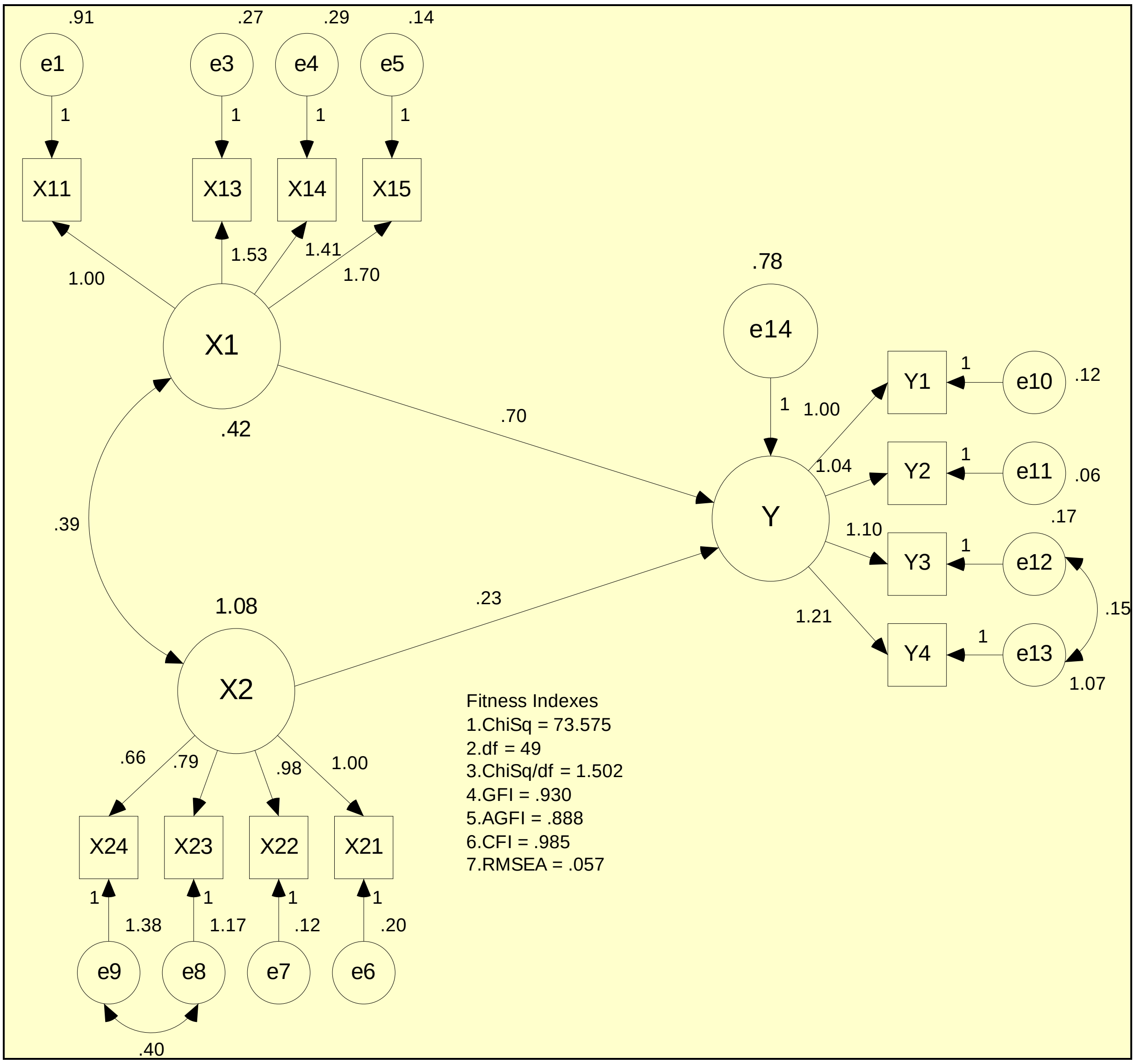

Figure 19: High Education Group: The output for Unconstrained Model.

The Chi-Square Value and DF for the Unconstrained Model

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	29	**73.575**	**49**	0.013	1.502
Saturated model	78	0.000	0		
Independence model	12	1760.721	66	0.000	26.678

Table 2b: The Moderation Test for High Education Group Data

	Constrained Model	Unconstrained Model	Chi-Square Difference	Result on Moderation	Result on Hypothesis
Chi-Square	**123.410**	**73.575**	**49.835**	Significant	Supported
DF	**50**	**49**	**1**		
GFI	0.884	0.930			
AGFI	0.819	0.888			
CFI	0.957	0.985			
RMSEA	0.097	0.057			
Chisq/df	2.468	1.502			
The hypothesis statement: Ha: Respondent's education moderates the relationship between X_2 and Y					Supported

*******The moderation test is significant since the Chi-Square difference between the constrained and unconstrained model is greater than 3.84. Recall: The Chi-Square value with 1 degree of freedom is 3.84.

Referring to Table 2b: All fitness indexes for the unconstrained model is significantly better (smaller Chi-Square) than the constrained model, indicating that the two group's coefficient differ.

The results show support for the hypothesis that education moderates the relationship between latent exogenous construct X_2 and its corresponding latent endogenous construct Y.

Once the moderation effect is established, the study might be interested to determine in which group (low education or high education) the relationship between X_2 on Y is more pronounced?

To address this particular research question, the researcher needs to run the unconstrained model separately using both datasets (Low Education and High Education). Compare the standardized parameter estimates and its significance for both datasets. The result is presented in Figure 21 for dataset 1 (low education), and Figure 22 for dataset 2 (high education).

7.8 COMPARING THE GROUP EFFECTS FOR A MODERATOR VARIABLE

Suppose one has the following research question to address: In which group (low education or higher education), the effect of moderator variable (education) is more pronounced? To address this RQ, the researcher needs to obtain the standardized estimate for the path of interest for both datasets. The procedure is demonstrated in Figure 20 and Figure 21.

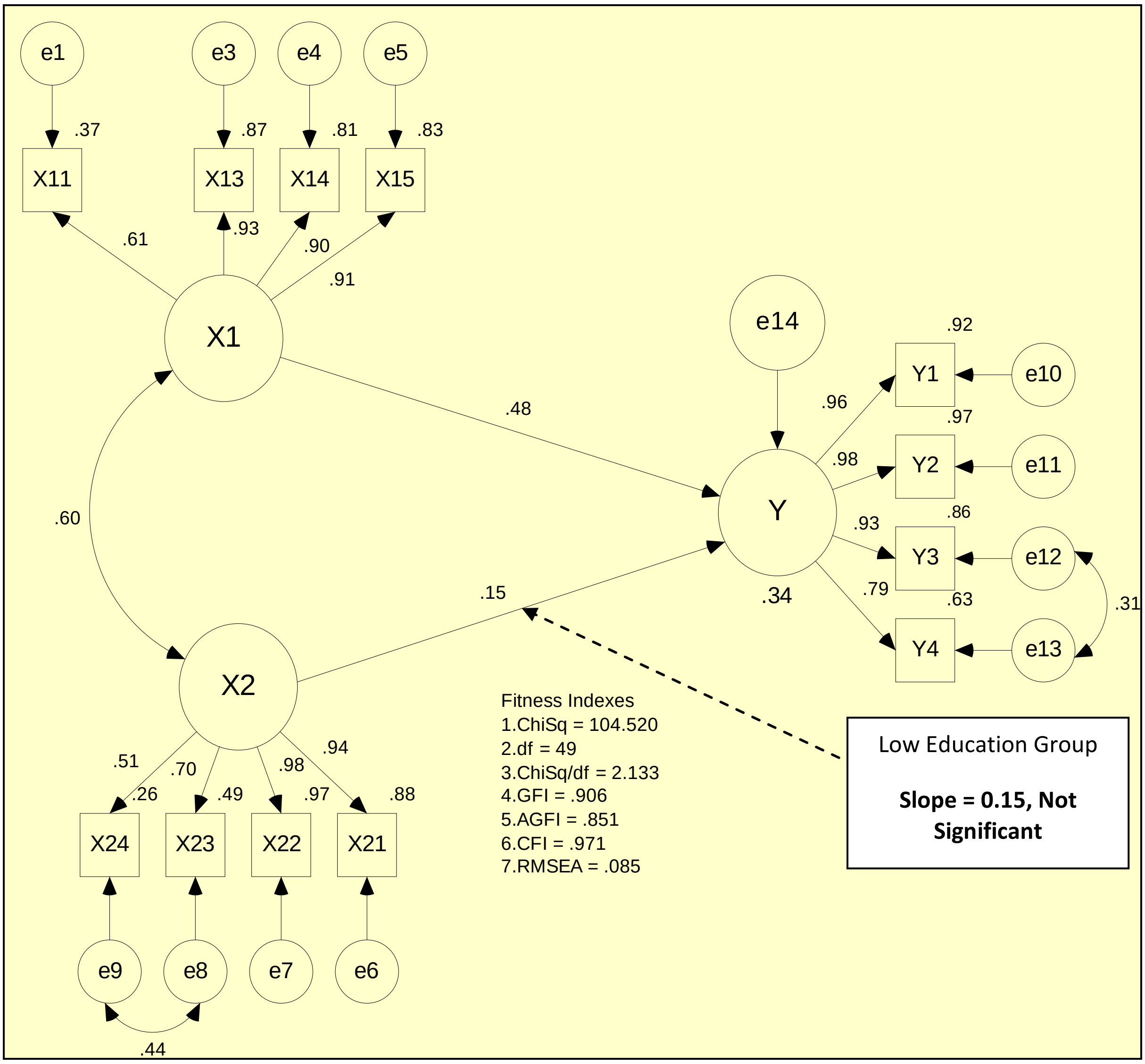

Figure 20: The Standardized Beta Estimate for Low Education Group in Path X_2 to Y

The Effect of X_2 on Y is Not Significant for "Low Education" Group

			Standardized beta Estimate	P	Result
Y	<---	X2	**0.15**	**0.077**	**Not Significant at 0.05**

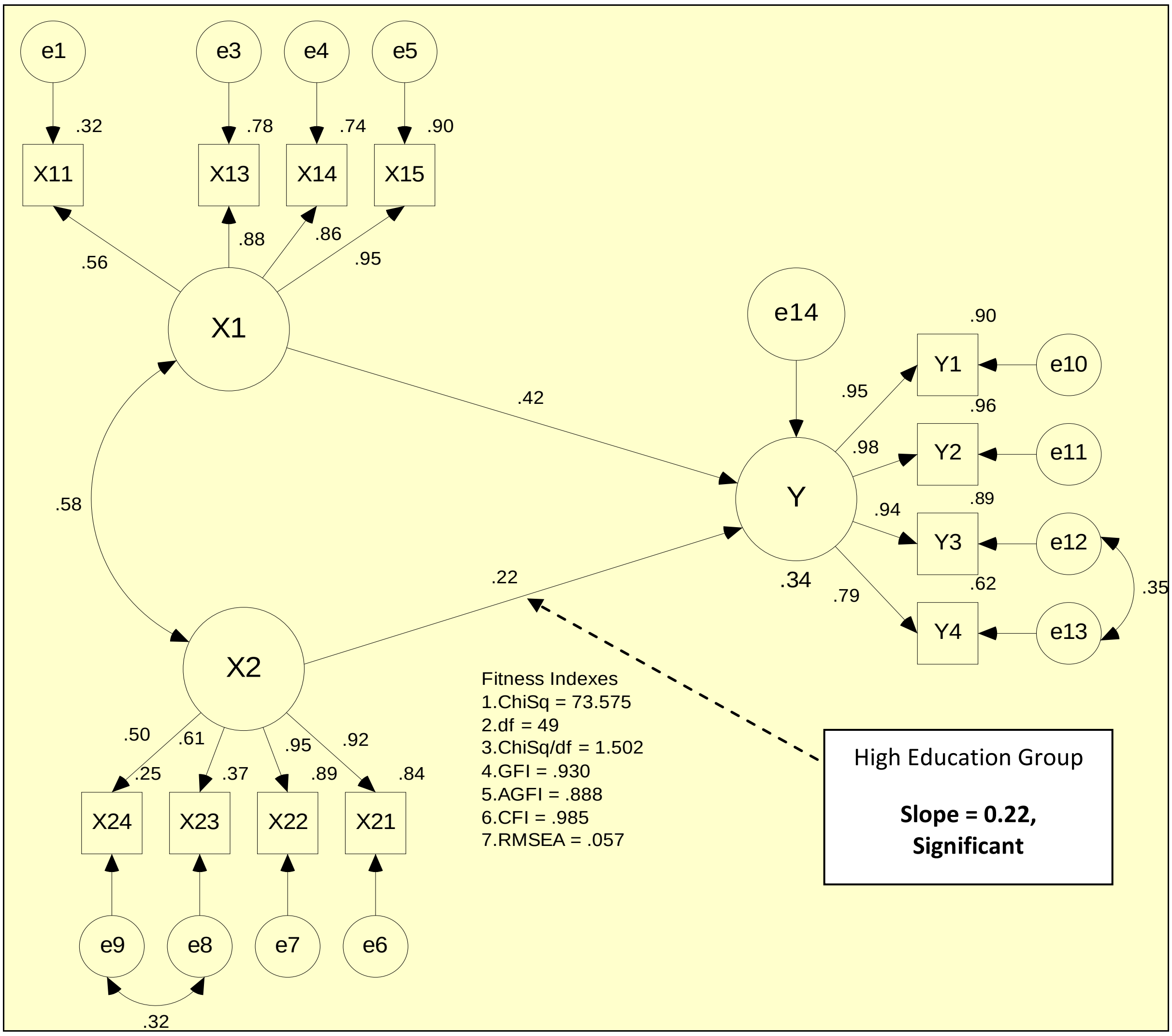

Figure 21: The Standardized Beta Estimate for High Education Group in Path X_2 to Y

The Effect of X_2 on Y is Significant for "High Education" Group

			Standardized beta Estimate	P	Result
Y	<---	X_2	**0.22**	**0.011**	**Significant at 0.05**

***The standardized parameter estimate for "High Education Group" is 0.22 while the same estimate for "Low Education Group" is 0.15. Thus, one can conclude that the effect of X_2 on Y is more pronounced in "Higher Education Group" compared to "Low Education Group".

Now the researcher wants to determine the type of moderation that occurs in the X_2 and Y relationship. The results show that the type of moderation is **full moderation** since the standardized estimate for **High Education** is **significant** while the standardize estimate for **Low Education** is **not significant**. If both estimates are significant then partial moderation occurs.