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Path Analysis to Determine the Effect of Learning Outcomes for Prerequisite Mathematics Courses on Expert Systems Courses

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Abstract

The study background is the need to evaluate learning and the placement of the sequence of courses. The learning objectives are achieved optimally. This study conducts a path analysis to determine the direct or indirect effect of learning outcomes for mathematics prerequisite courses, Discrete Mathematics and Linear Algebra and Matrix, on learning outcomes of Expert Systems with Artificial Intelligence as an intervening variable. This study is explanatory research conducted at the Study Program of Informatics Engineering, STMIK Palangkaraya. The sample used is the 2017 and 2018 batch of students who have taken and passed the MD, AL, KB, and SP courses, as many as 94 people. The data were analyzed using student learning outcomes in the four courses. The data were then selected and analyzed descriptively, the assumption of path analysis (normality, multicollinearity, and heteroscedasticity) was tested, and finally, path analysis was performed. Hypothesis testing was carried out with the help of the R program. The results showed (1) the learning outcomes of the MD and AL courses directly significantly affected the learning outcomes of the KB courses by 23% and 23.7%, respectively, and (2) the learning outcomes of the AL courses directly affected the learning outcomes of the SP courses by 34.9%, (3) the learning outcomes for MD and KB courses do not directly affect learning outcomes for SP courses, (4) learning outcomes for MD and AL courses do not indirectly affect learning outcomes for SP courses.

INTRODUCTION

As one factor that plays a vital role in influencing the process and learning outcomes, the curriculum is a design/program in higher education consisting of learning outcomes, mastered materials, learning strategies, and an assessment system [1]–[3]. The preparation of the curriculum structure in the form of course organization per semester needs to pay attention to the accuracy of the location of the courses that are adjusted to the consistent level of ability and integration between courses both vertically and horizontally. Organizing systems horizontally in semesters aims to broaden students' discourse and skills in a broader context. On the other hand, vertically managing this course aims to provide a depth of mastery for students so that predetermined graduate achievements can be realized.

One of the difficulties in organizing courses vertically is the proper placement of the sequence of courses to make it easier for students to follow the lectures that will be taken in the following semester. The determination of courses per semester and prerequisite courses shows the continuity of the curriculum in higher education. Prerequisite courses are mandatory requirements and must be taken by students before taking the next course. Similarities and subject interrelationships are decisive in preparing prerequisite courses [4], [5].

Through a curriculum that has been prepared, the Informatics Engineering Study Program (IT Study Program) STMIK Palangkaraya places several courses as prerequisites for other courses in the following semester. The Expert System (SP) is a compulsory subject for students of the IT Study Program STMIK Palangkaraya programmed in the fifth semester. To be able to take this course, students must go through an Artificial Intelligence (KB) course in the fourth semester. Meanwhile, to take this course, students must go through Discrete Mathematics (MD) systems in the second semester and Linear and Matrix Algebra (AL) courses in the third semester. The placement of this course sequence is presented in Figure 1.

Figure 1. Placement of Prerequisites for Expert System Courses

MD and AL courses as prerequisite courses include materials that are the mathematical basis for KB and SP courses, including logic and reasoning. This is reinforced by [6], which states that informatics is a collection of disciplines and techniques that process and manipulate discrete objects. Thus, MD can be the most fundamental science in informatics or computer science.

Investigating the effect of student learning outcomes in prerequisite courses on learning outcomes in advanced classes is essential to evaluate learning and curriculum, especially in the placement of course sequences, so that learning objectives are achieved. In their research, Paris, and Assidiqi [4] use path analysis to examine the effect of student mastery in prerequisite courses on Differential Equations courses. The research yielded the result that there were prerequisite courses that did not significantly affect the Differential Equation course. A similar study was conducted by Suhandiah and Hariadi [4], who used path analysis to determine the effect of prerequisite courses on the learning success of Database Programming (PBD) courses. The results obtained indicate that the prerequisite courses significantly influence the PBD courses. Shaffer *et al.* [7] test the hypothesis that learning content in prerequisite courses will improve learning in subsequent classes. The study results indicate that content only briefly discussed in prerequisite courses does not improve performance following procedures, and some topics may be removed from the system.

This study aims to conduct a path analysis to determine the direct or indirect effect of learning outcomes for mathematics prerequisite courses, namely Discrete Mathematics (MD) and Linear Algebra and Matrix (AL), on learning outcomes of Expert Systems (SP) with Artificial Intelligence (KB) as the intervention variable. Assumption testing is done using the R program because R is a powerful language and environment for statistical and graphic computing [8]. In addition, R is a freeware that is open source, and there is plenty of help available online.

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METHOD

This survey research with a quantitative approach explains causality between variables through hypothesis testing (explanatory). The population in this study was 135 students of STMIK Palangkaraya IT Study Program in 2017 and 2018, while the sample used was 2017 and 2018 students who had taken and passed the MD, AL, KB, and SP courses, many as 94 people. This study was carried out for two semesters, starting from April 2020 to February 2021, at the IT Study Program STMIK Palangkaraya. The author uses secondary data for this study in the form of final grades for MD, AL, KB, and SP courses obtained from the Academic and Student Affairs section of STMIK Palangkaraya. This study has two independent variables (exogenous), one intervening variable, and one dependent variable (endogenous). The exogenous variables are learning outcomes for MD courses (X_1) and AL courses (X_2), the intervening variable is learning outcomes for family planning courses (Y_1) while the endogenous variable is learning outcomes for SP courses (Y_2).

The author uses path analysis to analyze the data of this study. The path analysis assumption test is carried out based on the main assumptions of multiple linear regression, namely normality and heteroscedasticity tests on residual variables and multicollinearity tests on residual values between exogenous variables [9], [10].

RESULTS AND DISCUSSION

1. Description of Learning Outcomes

The learning outcomes of 135 students in the MD, AL, KB, and SP courses are presented in a table with the categories of A ($80 \leq X_1 \leq 100$), B (70 $\leq X_1 < 80$), C ($56 \leq X_1 < 70$, D ($40 \leq X_1 < 56$), and E ($0 \leq X_1 < 40$) grades.

Table 1. Recapitulation of Learning Outcomes for Discrete Mathematics Courses

	Score				
	A	B	C	D	E
Amount	23	67	41	3	1
Percent	17%	49.6%	30.4%	2.2%	0.7%

Table 1 shows that 97.1% passed the MD course. Thus, as many as 131 students are considered capable of analyzing and solving problems by applying the material that has been delivered during the MD course and can take the AL course.

Table 2. Recapitulation of Learning Outcomes for Linear Algebra and Matrix Courses

	Score				
	A	B	C	D	E
Amount	42	78	12	2	1
Percent	81.1%	57.8%	8.9%	1.5%	0.7%

Table 2 shows that 97.8% of students passed the AL courses. Thus, as many as 132 students are considered capable of understanding AL courses and can take family planning courses.

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Table 3. Recapitulation of Learning Outcomes for Artificial Intelligence Courses

	Score				
	A	B	C	D	E
Amount	77	41	16	0	1
Percent	57%	30.4%	11.9%	0%	0.7%

Table 3 shows that 99.3% of students passed the family planning courses. Thus, as many as 134 students are considered capable of understanding family planning courses and can take SP courses.

Table 4. Recapitulation of Learning Outcomes of Expert System Courses

	Score				
	A	B	C	D	E
Amount	88	38	6	0	3
Percent	65.2%	28.1%	4.4%	0%	2.2%

Table 4 shows that 97.8% passed the SP courses. Thus, as many as 132 students are considered able to understand and apply the material obtained during the SP courses.

Furthermore, the initial data selection was carried out on the number of students, selected students who had taken and passed the MD, AL, KB, and SP courses, as many as 94 students. The graduation requirement is that students get a minimum grade of C. The description of the data can be seen in Table 5.

Table 5. Recapitulation of Learning Outcomes for Discrete Mathematics Courses, Linear and Matrix Algebra, Artificial Intelligence, and Expert Systems

MK	Score			mean	stdv.
	A	B	C		
MD	17 18.1%	43 45.7%	34 36.2%	70.24	7.98
AL	33 35.1%	54 57.4%	7 7.4%	74.99	6.61
KB	56 59.6%	29 30.9%	9 9.6%	81.09	7.36
SP	67 71.3%	24 25.5%	3 3.2%	82.81	6.11

Table 5 shows that students' understanding based on learning outcomes obtained is the highest for the Expert System course, with an average value of 82.81 and a standard deviation of 6.11.

2. Path Analysis of Learning Outcomes for SP.

Path analysis is used in this study because the author considers this method the most appropriate way to analyze the effect of learning outcomes for mathematics prerequisite courses on learning outcomes for the Expert Systems course with Artificial Intelligence as the intervening variable. This is reinforced by [11] which states that path analysis is intended to determine the effect of exogenous variables on endogenous variables, either directly or indirectly. This research path diagram is shown in Figure 2.

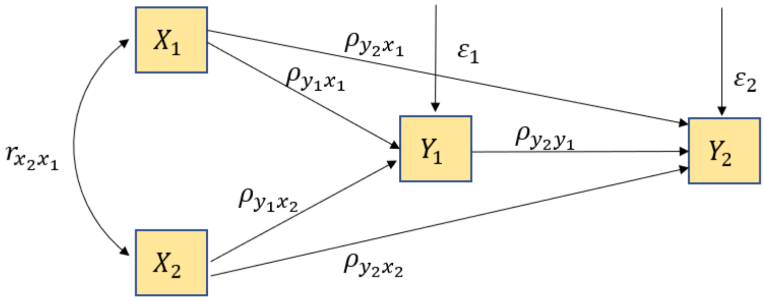

Figure 2. Path Diagram of the Effect of Learning Outcomes for Prerequisite Mathematics Course on the Learning Outcomes of the Expert System Course

Based on the path diagram in Figure 2, the equations for substructure one and substructure two can be determined according to equations (1) and (2).

$$Y_1 = \rho_{y_1x_1}X_1 + \rho_{y_1x_2}X_2 + \varepsilon_1 \quad (1)$$

$$Y_2 = \rho_{y_2x_1}X_1 + \rho_{y_2x_2}X_2 + \rho_{y_2y_1}X_2 + \varepsilon_2 \quad (2)$$

Residual Assumption Test Results

The main assumptions that need to be tested in path analysis, according to Nurmawati and Kismiantini [9] are based on the premise of multiple linear regression, namely, the residual values are normally distributed, the residual values between exogenous variables are not correlated, and the residual values of exogenous variables have the same variance. Testing the path analysis residual assumptions in this study was carried out by utilizing the R program.

Normality Test

Whether normally distributed or not, data can be known by doing a normality test on the data. In path analysis, the normality test is performed on the residual variables in each substructure, a multiple linear regression model, and determines whether the confounding variables or residuals are normally distributed in each model. If the p-value is ≥ 0.05, the data is normally distributed. Otherwise, if the p-value is <0.05, the information is not normally distributed. The author uses a research sample of > 50, according to Mishra *et al.* [12]The proper residual variable normality test to be carried out is the Kolmogorov-Smirnov Normality Test.

The distribution of residual variables in the substructure1 and substructure two models can be seen in Figure 3.

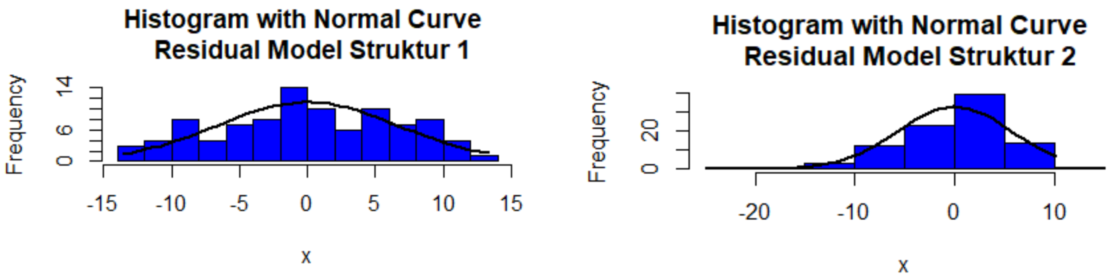

Figure 3. Histogram with Normal Distribution Curve for Residual Variables (a) Substructure Model 1, (b) Substructure Model 2

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There is a symmetrical curve in both Figure 3(a) and Figure 3(b) which indicates that the data (residual variables) in both the substructure model 1 and substructure model 2 are normally distributed. Observation of the curve to determine the normality of this data still needs to be tested again for normality using the *Kolmogorov Smirnov test*. Normality test results on the residual variables in the substructure one and substructure two models using R are presented in Table 6.

Table 6. Normality Test Results for Residual Variables
on Substructure Model 1 and Substructure Model2

Residual Variable	p-value	Decision
Substructure Model 1	0.8085	Normal distribution
Substructure Model 1	0.4239	Normal distribution

Table 6 shows that the residual variables in the substructure one and substructure two models are normally distributed.

Multicollinearity Test

Multicollinearity is a multiple linear regression model that indicates a linear correlation between exogenous variables [13]. The multicollinearity test on the substructure model 1 was used to determine whether multicollinearity existed between discrete mathematical variables and linear and matrix algebra. In contrast, the multicollinearity test on the substructure model 2 was used to determine whether multicollinearity existed between discrete mathematics variables, linear algebra, matrices, and artificial intelligence.

The value of VIF (Variance Inflation Factor) determines the presence or absence of multicollinearity symptoms. If the VIF value is less than 10.00, the regression model does not have a multicollinearity problem. The results of the multicollinearity test on substructure model 1 and substructure model 2 using R are presented in Table 7.

Table 7. Multicollinearity Test Results on Substructure Model 1
and Substructure Model 2

Exogenous Variable		VIF	Decision
Substructure Model 1	X_1	1.242	There is no multicollinearity
	X_2	1.242	
Substructure Model 1	X_1	1.304	There is no multicollinearity
	X_2	1.308	
	Y_1	1.186	

Table 7 shows no multicollinearity problem in the exogenous variables in both the substructure model 1 and the substructure model 2.

Heteroscedasticity Test

A heteroscedasticity test was carried out to determine whether there was an inequality of variance in a regression model from the residuals of one observer to another observer [14]. The regression model is said to be good if the variance is homoscedasticity. The author uses the Breusch Pagan Godfrey Test in this test because this testing technique has better accuracy [15]. Heteroscedasticity test decision making using R, namely: H_0 is rejected if the p-value < 0.05, which

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means the variance is heteroscedasticity. Table 8 presents the results of the heteroscedasticity test with R.

Table 8. Heteroscedasticity Test Results on Residual Variables on Substructure Model 1 and Substructure Model2

Variable Residual	p-value	Decision
Substructure Model 1	0.08772	Variance is homoscedasticity
Substructure Model 1	0.3823	Variance is homoscedasticity

Based on the test results in Table 8, it can be concluded that the regression model of substructure one and substructure two is good because the variance is homoscedasticity.

Path Coefficient

The path coefficient is used to determine the magnitude of the relationship between variables. The path coefficient estimation is carried out with the help of R. The path coefficient estimation results are presented in Table 9.

Table 9. Path Coefficient Estimation Results

Variable Relationship	Path Coefficient
X_1 to Y_1	0.230
X_2 to X_1	0.237
$X_1$to Y_2	0.020
$X_2$to Y_2	0.307
$Y_1$to Y_2	0.060

Based on the path coefficient values obtained in Table 9, the equations of the substructure model 1 (Equation 1) and the structural model 2 (Equation 2) become Equation (3) and Equation (4).

$$Y_1 = 0{,}230X_1 + 0{,}237X_2 + \varepsilon_1 \quad (3)$$
$$Y_2 = 0{,}02X_1 + 0{,}307X_2 + 0{,}06X_2 + \varepsilon_2 \quad (4)$$

Model Validity Test

Testing the model's validity in path analysis can use the coefficient of determination and the trimming method. The coefficient of decision is used to determine the model's adequacy in explaining the variation in the data set [16]. The total diversity of data that the model can define according to [17] is indicated by the coefficient of absolute determination as in equation (5).

$$R_t{}^2 = 1 - \varepsilon_1{}^2\varepsilon_2{}^2 \ldots \varepsilon_n{}^2 \quad (5)$$

while the effect of the residual or residual can be calculated using the formula Equation (6).

$$\varepsilon_i{}^2 = \sqrt{1 - R_i{}^2}, \text{ i=1,2,3,…,n} \quad (6)$$

where $R_t{}^2$is the coefficient of total determination, $R_i{}^2$is the coefficient of determination of each equation, and ε_i is the effect of the residual or residual of each equation.

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The calculation results with R provide the values of the coefficient of determination for substructure model 1 and substructure model 2, as presented in Table 10.

Table 10. Coefficient of Determination of Substructure Model 1 and Substructure Model 2

	Coefficient of Determination (R^2)
Substructure Model 1	0.157
Substructure Model 1	0.117

The coefficient of determination of each model, as presented in Table 10, is used to calculate the coefficient of total resolution. The coefficient of accurate determination is an indicator of the model's validity. Based on Table 10, it can be continued with calculations as in equations (7) and (8).

1) 1 . substructure model
   known $R^2 = 0{,}157$that the residual coefficient of the substructure model 1:
   $$\varepsilon_1 = \sqrt{1 - R^2}$$
   $$= \sqrt{1 - 0{,}157} = 0{,}9182 \qquad (7)$$
2) 2 . substructure model
   known $R^2 = 0{,}157$that the residual coefficient of the substructure model 2:
   $$\varepsilon_2 = \sqrt{1 - R^2}$$
   $$= \sqrt{1 - 0{,}117} = 0{,}9397 \qquad (8)$$
3) Based on the results obtained in Equations (7) and (8) and the formula in equation (5), the coefficient of total determination is obtained according to equation (9).
   $$R_t{}^2 = 1 - \varepsilon_1{}^2 \varepsilon_2{}^2$$
   $$= 1 - (0.9182)^2 (0.9397)^2 \qquad (9)$$
   $$= 1 - (0.8431)(0.883)$$
   $$= 0.2555.$$

The value of the coefficient of total determination in equation (9) is 0.2555, which means that this path analysis explains the whole diversity of the variable learning outcomes of Expert Systems by 25.55%.

Path Analysis Hypothesis Test Results

Hypothesis testing is used to test the significance of the path coefficients partially. The tested hypothesis is formulated as follows:

H_0: $\rho_{yx} = 0$ (the direct effect is not significant)

H_1: $\rho_{yx} \neq 0$(the direct effect is significant)

The test results using the R program are shown in Table 11.

Table 11. Hypothesis Testing Results

Variable Relationship	Path Coefficient	p-value	Decision
X_1 to Y_1	0.230	0.028	Significant
X_2 to X_1	0.237	0.023	Significant
X_1 to Y_2	0.020	0.858	Not significant
X_2 to Y_2	0.307	0.005	Significant
Y_1 to Y_2	0.060	0.563	Not significant

Based on the test results in Table 11, a partial analysis can be carried out on the substructure model 1 and substructure model 2.

Analysis of the Substructure Model 1

1. The Effect of Discrete Mathematics Learning Outcomes on Artificial Intelligence Course Learning Outcomes

   The tested hypotheses are:

   H $_0$: $\rho_{y_1x_1} = 0$(direct effect X_1onY_1 not significant)

   H $_1$: $\rho_{y_1x_1} \neq 0$(direct influence X_1onY_1 significant)

   Based on Table 11, the p-value = 0.028 is smaller than the significance level $\alpha = 0{,}05$. Thus H $_{0 \text{ is}}$ rejected, and H $_1$ is accepted, meaning the path coefficient is significant. So, learning outcomes for MD courses directly have a significant effect on family planning learning outcomes.

2. The Effect of Linear Algebra and Matrix Learning Outcomes on Artificial Intelligence Course Learning Outcomes

   The tested hypotheses are:

   H $_0$: $\rho_{y_1x_2} = 0$(direct effect X_2onY_1 not significant)

   H $_1$: $\rho_{y_1x_2} \neq 0$(direct influence X_2onY_1 significant)

   Based on Table 11, the p-value = 0.023 is smaller than the significance level $\alpha = 0{,}05$. Thus H $_{0 \text{ is}}$ rejected, and H $_1$ is accepted, meaning the path coefficient is significant. So, learning outcomes for AL courses directly have a significant effect on family planning learning outcomes. Thus the equation of the substructure model 1 according to Equation (3) becomes equation (10).

   $$Y_1 = 0{,}230X_1 + 0{,}237X_2 + 0{,}9182 \quad (10)$$

   Furthermore, based on the test results with R, the correlation value between $X_1$and and $X_2$the $r_{x_2x_1} = 0{,}44$coefficient of determination $(R^2)$is 0.157, which indicates that the contribution of $X_1$and $X_2$to $Y_1$is 15.7%, and the remaining 84.3% is the contribution of other factors not included in this study.

The path diagram illustrating the substructure model 1 is shown in Figure 4.

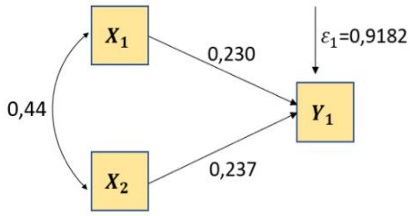

Figure 4. Substructure Model Path Diagram 1

Analysis of the 2 Substructure Model

1. The Effect of Discrete Mathematics Learning Outcomes on Learning Outcomes of Expert Systems Courses

   The tested hypotheses are:

   H $_0$: $\rho_{y_2x_1} = 0$(direct effect X_1onY_2 not significant)

   H $_1$: $\rho_{y_2x_1} \neq 0$(direct influence X_1onY_2 significant)

   Based on Table 11, the p-value = 0.858 is more significant than the significance level $\alpha = 0{,}05$. Thus H $_{0\text{ is}}$ accepted, meaning the path coefficient *is* not significant. So, the learning outcomes of MD courses do not directly have a significant effect on SP learning outcomes.

2. The Effect of Learning Outcomes for Linear Algebra and Matrices on Learning Outcomes for Expert Systems Courses

   The tested hypotheses are:

   H $_0$: $\rho_{y_2x_2} = 0$(direct effect X_2onY_2 not significant)

   H $_1$: $\rho_{y_2x_2} \neq 0$(direct influence X_2onY_2 significant)

   Based on Table 11, if the p-value = 0.005 is less than the significance level $\alpha = 0{,}05$, then H $_{0\text{ is}}$ accepted, meaning the path coefficient is significant. Thus the learning outcomes of AL courses directly have a significant effect on SP learning outcomes.

3. The Effect of Learning Outcomes on Artificial Intelligence Courses on Learning Outcomes of Expert Systems Courses

   The tested hypotheses are:

   H $_0$: $\rho_{y_2y_1} = 0$(direct effect X_1onY_2 not significant)

   H $_1$: $\rho_{y_2y_1} \neq 0$(direct influence X_1onY_2 significant)

   Based on Table 11, the p-value = 0.563 is more significant than the significance level $\alpha = 0{,}05$. Thus H_0 is accepted, meaning the path coefficient is insignificant. So, learning outcomes for family planning courses have no significant direct effect on SP learning outcomes.

The path diagram illustrating the substructure model 2 is shown in Figure 5.

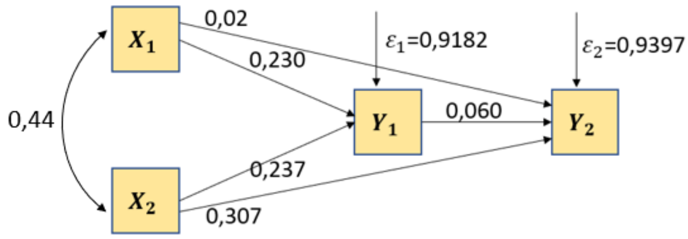

Figure 5 . Substructure Model Path Diagram 2

The results of the analysis prove that there are insignificant path coefficients, namely variables $X_1$and Y_1, therefore the substructure model 2 needs to be improved through the Trimming Method, which excludes variables X_1 and Y_1 those that are considered to be insignificant path coefficients, then retested by excluding variables X_1 and Y_1.

The results of calculations using the R program for the improved substructure model 2 are presented in Table 12.

Table 12. Results of Hypothesis Testing for Substructure Model 2 with *trimming*

Variable Relationship	Path Coefficient	p- value	Decision
X_2 to Y_2	0.349	0.000	significant

The magnitude of the coefficient of determination (R^2) obtained by 0.122 indicates the contribution of the effect of learning outcomes for AL. Courses on learning outcomes for SP. Courses are 12.2 %, and the remaining 87.8 % contribute to other factors not included in the study. Furthermore, the residual coefficient of the substructure model 2 can be calculated by *trimming* as in equation (8).

$$\varepsilon_2 = \sqrt{1 - R^2} = \sqrt{1 - 0{,}122} \quad = \sqrt{0{,}878} = 0{,}9370 \tag{11}$$

Furthermore, the substructure model equation 2 states the empirical causal relationship between the paths $X_2$to Y_2Equation (4) after *trimming* becomes Equation (12).

$$Y_2 = 0{,}349X_2 + 0{,}9370 \tag{12}$$

The path diagram of the substructure model 2 has changed to Figure 6.

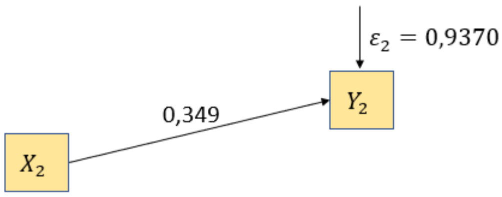

Figure 6. Substructure Model Path Diagram 2 with Trimming

Thus, the path diagram of the effect of learning outcomes for mathematics prerequisite courses on learning outcomes for Expert Systems courses in full after trimming is shown in Figure 7.

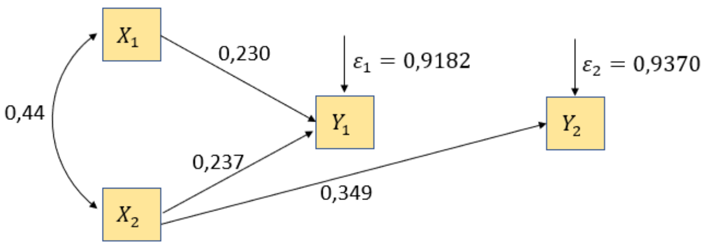

Figure 7. Path Diagram of the Effect of Variables X_1 and X_2 on Variables Y_2 with Variables Y_1 as Intervening Variables with Trimming

This study indicates that learning outcomes for family planning courses have no significant direct effect on learning outcomes for SP courses, which are indicated by the acquisition of an insignificant path coefficient. The absence of a significant impact of a prerequisite course on a follow-up course can occur due to various factors, one of which has been explained in the research results of Shaffer [7]. An expert system is one of the artificial intelligence applications in real life, which has an extensive work area [18]–[20]. In other words, students' success in family planning courses should be able to support their success in taking SP courses. The data used in this study were not obtained from the measurement results but the results of the final assessment of each course lecturer consisting of many assessment components. This is a weakness of this study. The impact study program managers motivate lecturers to optimize learning and evaluate the assessment system so that the learning objectives set can be adequately achieved and student abilities can be measured, and the results are known well.

CONCLUSIONS AND SUGGESTIONS

The test results on the substructure model 1 show that learning outcomes for MD courses and AL courses directly have a significant and positive relationship to learning outcomes for family planning courses with 23% and 23.7%, respectively. The test results on the substructure model 2 show that only the LA learning outcome variable directly has a significant and positive relationship to the SP course learning outcomes with 34.9%, while the MD and KB course learning outcomes variables do not directly affect the learning outcomes of SP courses.

The results obtained in this study indicate that there is no direct effect of learning outcomes for family planning courses as an intervening variable on learning outcomes for SP courses. As a result, there is no indirect effect on learning outcomes for MD courses and learning outcomes for AL courses on SP learning outcomes.

Furthermore, the test results also show that this path analysis explains the total diversity or contribution of the MD, AL, and KB learning outcomes variables in influencing the SP course learning outcomes by 25.55%. The use of secondary data in this study, namely the final grades of students in each course which consists of many assessment components, is a weakness of this study; therefore, it is better to use primary data in the form of measurement results to determine the ability of students in each subject in further research.

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