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Factor Influencing Delayed Completion in Mathematics Students at Nusa Cendant University: A Factor Analysis Approach

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ABSTRACT

This study aimed to identify and analyze factors contributing to the delay in the study period of students enrolled in the Mathematics Program at the Faculty of Science and Engineering (FST), Nusa Cendana University (UNDANA). The research employed a comprehensive analytical approach, starting with validity and reliability tests, followed by descriptive analysis, and culminating in factor analysis. Initially, 27 variables were considered; however, after conducting validity and reliability assessments, 18 variables were deemed suitable for further analysis. These 18 variables were subjected to factor analysis, revealing that they could be consolidated into four distinct factors, collectively accounting for 68.734% of the total variability observed among the students. The four identified factors influencing study delays are (1) student and supervisor commitment to completing the final project, (2) campus and peer support, (3) intelligence and discipline, and (4) motivation and relationships. Among these, the commitment of students and their supervisors to the timely completion of the final project emerged as the most dominant factor, demonstrating 43.417% of the total variance. The findings highlight the crucial role of both individual dedication and external support systems in ensuring timely academic progress, offering valuable insights for improving student outcomes in the Mathematics Program at UNDANA.

1. Introduction

Nusa Cendana University (UNDANA) is a public university located in the city of Kupang, East Nusa Tenggara Province (NTT). Among the numerous study programs offered at UNDANA, the Mathematics Study Program of the Faculty of Science and Engineering (FST) continues to face challenges related to delays in the completion of student studies. The strategic plan (*rencana strategis*, RENSTRA) of the Mathematics Program at FST UNDANA for 2019-2023 has been carefully formulated to address this challenge. Data from the Study Program Performance Report (*laporan kinerja program studi*, LKPS) of the Mathematics Program at FST UNDANA shows that the average study duration for students graduating in 2016, 2017, and 2018 was 4,53; 4,73; and 4,33 years, respectively. Although the average study completion time is still around four years, field data indicated that in the odd semester of 2022, there were 24 eighth-semester students who were only at the proposal stage of their final assignments. This inevitably leads to an accumulation of students in the study program, significantly impacting the accreditation of the program.

It is widely recognized that student learning outcomes are influenced by two main factors: internal factors arising from the students and environmental factors [1]. Economic factors also contribute to delays in the completion of student studies. On the other hand, a study on students of the Faculty of Mathematics and Natural Sciences (FMIPA) at the State University of Makassar (UNM) identified four factors hindering study completion: internal and learning factors, self-readiness and potential, economic and campus management factors, and external societal environment factors [2]. Similar studies on economics students found that internal factors, external factors, societal environment, and school environment influence the delay in study completion [3].

Factor analysis can be used to examine the influence of these factors on the study duration of mathematics students at UNDANA. This analysis is a statistical technique used to understand the structure within the data by identifying patterns or latent factors that might cause correlations between observed variables [4]. In addition to reducing the number of variables, factor analysis can also identify the most dominant factors affecting an issue [5].

2. Method

2.1. Factor Analysis

Factor analysis can be employed to examine the impact of these factors on the study duration of students in the Mathematics Program at UNDANA. Factor analysis explains the variation in a set of original variables using fewer latent factors, assuming that all original variables can be expressed as linear combinations of these factors plus residual terms [6]. An observed random variable *X*, with *p* components, has a mean vector *μ* and covariance matrix *Σ*. The factor model postulates that *X* linearly depends on some unobserved random variables $F_1, F_2, \dots, F_m$ known as common factors, and *p* additional sources of variance $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_p$ referred to as errors or specific factors. Specifically, the factor analysis model is as follows [7]:

$$\begin{aligned} X_1 - \mu_1 &= L_{11}F_1 + L_{12}F_2 + \cdots L_{1m}F_m + \varepsilon_1 \\ X_2 - \mu_2 &= L_{21}F_2 + L_{22}F_2 + \cdots L_{2m}F_m + \varepsilon_2 \\ &\vdots \\ X_p - \mu_p &= L_{P1}F_1 + L_{P2}F_2 + \cdots L_{Pm}F_m + \varepsilon_P \end{aligned} \tag{1}$$

or in matrices notation:

$$\boldsymbol{X} - \boldsymbol{\mu}_{(p\times l)} = \boldsymbol{L}_{(p\times m)}\boldsymbol{F}_{(m\times p)} + \boldsymbol{\varepsilon} \tag{2}$$

where,
X_i = random vector with *p* components on observation *i*
μ_i = mean of variable *i*
L_{ij} = factor loading of variable i and factor *j*
F_j = common factor *j*
ε_i = residual or error of variable *i*.

Assuming that:

a. $E[F] = 0_{(m\times 1)}, Cov[F] = E[FF'] = I_{(m\times m)}$
b. $E[\varepsilon] = 0_{(p\times 1)}, Cov[\varepsilon] = E[\varepsilon\varepsilon'] = \psi_{(p\times p)}$
c. F and ε are independent, then $Cov[\varepsilon, F] = E[\varepsilon F'] = 0_{(p\times m)}$. Where ψ are diagonal matrices.

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The assumption in relation to (2) represents an orthogonal factor model, which in matrix notation is written as follows:

$$\boldsymbol{X}_{(\boldsymbol{p}\times\boldsymbol{l})} = \boldsymbol{\mu}_{(\boldsymbol{p}\times\boldsymbol{l})} + \boldsymbol{L}_{(\boldsymbol{p}\times\boldsymbol{m})}\boldsymbol{F}_{(\boldsymbol{m}\times\boldsymbol{l})} + \boldsymbol{\varepsilon}_{(\boldsymbol{p}\times\boldsymbol{l})} \quad (3)$$

This statistical technique helps to understand the underlying structure within data by identifying patterns or latent factors that may cause correlations among observed variables. In addition to reducing the number of variables, factor analysis can also reveal the most dominant factors influencing a particular issue [8].

This study utilized factor analysis to investigate the factors contributing to delays in completing students' studies within the mathematics program. Factor analysis was chosen because it can uncover underlying patterns in data and simplify complex datasets into key factors that are more easily understandable. Additionally, this method ensures the validity and reliability of the variables used, thereby producing robust and credible findings.

Various studies have explored the application of factor analysis in different contexts. For instance, research demonstrated that factor analysis effectively identified the dominant factors influencing the academic performance index of undergraduate Mathematics students at the Faculty of Mathematics and Sciences at the University of North Sumatra (FMIPA USU) [5]. Their findings underscored the utility of factor analysis in discerning critical factors that impact student success in academic settings. Another study discussed the application of Procrustes analysis in factor rotation methods, highlighting varimax, equamax, and quartimax as the most appropriate techniques [8]. This research emphasized the importance of choosing an optimal rotation method to enhance the interpretability of factor analysis results, ensuring more precise insights into complex relationships among variables. Furthermore, another study explored factor analysis using data integration techniques such as proportional and differential shifts [9]. This study focused on identifying a single significant factor influencing economic growth rates in the Brebes Regency. This approach illustrates how factor analysis can be adapted and applied across diverse fields to uncover pivotal factors driving specific outcomes, thereby contributing valuable insights for policy-making and strategic planning

Overall, these studies collectively underscore the versatility and effectiveness of factor analysis as a powerful statistical tool for exploring and understanding complex relationships within datasets, making it particularly relevant and beneficial for studying issues such as student academic performance and economic growth.

2.2. Data

The data used was primary data obtained through questionnaires completed by 80 students of the Mathematics Program, FST UNDANA, active students in semesters 9, 11, and 13, and alums from the 2016 – 2019 cohorts who graduated after the 8th semester.

2.3. Research Variables

The variables discussed in this research were components obtained based on references from previous studies.

Table 1. Variables for Measuring Factors Affecting Study Delays

Variables	Definition	Variables	Definition
X_1	clean and green campus environment	X_{16}	relationships between students and faculty members
X_2	quiet and comfortable learning environment	X_{17}	relationships among students
X_3	counseling and career support	X_{18}	living environment
X_4	availability of adequate library facilities	X_{19}	social interactions with peers
X_5	availability of learning facilities (desks, chairs, LCD, whiteboard, markers, etc.)	X_{20}	supervisors and students collaborate to make research decisions
X_6	availability of fast internet access	X_{21}	students receive critical and constructive feedback from supervisors in the process of completing their final assignments

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Variables	Definition	Variables	Definition
X_7	availability of easily accessible administrative services	X_{22}	supervisors pay attention to students' academic progress
X_8	level of intelligence and talent	X_{23}	students revise their final assignments optimally
X_9	interest	X_{24}	students enjoy writing and researching
X_{10}	level of student discipline	X_{25}	students easily determine their thesis topics
X_{11}	students pursue a bachelor's degree for prestige and status	X_{26}	students easily obtain research data
X_{12}	students pursue a bachelor's degree to enhance their competence and intellectual capacity	X_{27}	students' skills in using the internet and campus information systems to find literature
X_{13}	students pursue a bachelor's degree because they receive a scholarship		
X_{14}	relationships with family members		
X_{15}	the family's economic condition is very good, allowing students to focus on completing their studies		

The aspect influenced by these variables in this study is the delay in student studies. The variables used to measure the factors affecting the delay in the study period are listed in Table 1. The questionnaires were distributed using Google Forms, which were shared via WhatsApp to the class representatives of each cohort to be forwarded to the targeted respondents.

2.4. Research Procedures

Meanwhile, the factor analysis process can be carried out with the following steps:

a. Calculating the correlation matrix using Bartlett's test of sphericity and measuring MSA (measure of sampling adequacy) [4].

- Bartlett's Test of Sphericity

  If the calculated Bartlett value > the Bartlett table value, or the significance < α 5%, it indicates significant correlation among the variables analyzed, and the process can proceed [10]. The Bartlett test formula can be seen in the following:

  $$X^2 = -\left[(N-1) - \frac{(2p+5)}{6}\right]\ln|R| \quad (4)$$

  With degree of freedom as follows,

  $$df = \frac{p(p-1)}{2} \quad (5)$$

  where

  N = the number of observations

  p = the number of variables

  $|R|$ = determinant of correlation matrix.

- Keiser-Meyer-Olkin (KMO)

  KMO values ranging from 0.5 to 1.0 indicate that the analysis process is appropriate and can be continued. In Statistical Package for the Social Sciences (SPSS), the sampling adequacy measure for each variable is displayed on each diagonal in the anti-image correlation matrix [11]. KMO test formula:

  $$KMO = \frac{\Sigma\Sigma_{i=j} r_{ij}^2}{\Sigma\Sigma_{i=j} r_{ij}^2 + \Sigma\Sigma_{i=j} a_{ij}^2} \quad ; i = 1,2,\dots,p \, ; j = 1,2,\dots,p \quad (6)$$

  where

  r_{ij} = simple correlation coefficient between variable i and variable j

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a_{ij}= partial correlation coefficient between variable i and variable j.

- Measure of Sampling Adequacy (MSA)

  MSA is an index comparing the partial correlation coefficients for each variable. It is used to measure the adequacy of the sample [12]. The MSA statistic is as follows:

$$MSA = \frac{\sum r_{ij}^2}{\sum r_{ij}^2 + \sum a_{ij}^2} \quad (7)$$

where

r_{ij} = simple correlation coefficient between variable i and variable j

a_{ij}= partial correlation coefficient between variable i and variable j.

b. Extraction or factoring process

The factor extraction method used in this research is the Principal Component Analysis (PCA) method[13]. When extracted from the correlation matrix, the PCA approach yields factors with the following criteria:

- Communalities represent the amount of variance of a variable that is shared with other variables.
- Eigenvalues with their characteristic equations.

c. Determining the number of factors.

The number of factors is determined based on the eigenvalues of each emerging factor. The core factors selected are those with eigenvalues > 1[10].

d. Rotating the factors

Factor rotation is performed to facilitate interpretation by determining which variables are listed within a factor, as sometimes several variables have high correlations with more than one factor, or if some factor loadings of the variables are below a predetermined threshold [14].

e. Determining factor scores.

Factor scores are the values for the unobserved random factors $Fj'jj = 1,2, \dots, n$. Thus, the factor score fj (case j) is an individual measure on the factor, which is a weighted average value [15].

3. Result and Discussion

3.1. Validity and Reliability Testing

Through validity testing, 18 out of 27 variables were found to be valid. Through Cronbach's Alpha test in Table 2, a value of 0.923 was obtained, which is greater than 0.70, indicating that the variables in the study were strongly interrelated and consistent. This suggests that the measurement instrument used to assess these variables in the study is reliable and can produce consistent results if the measurement is repeated [16]. Therefore, the variables that have been deemed valid and reliable can proceed to the factor analysis process.

Table 2. Cronbach's Alpha Coefficients

Reliability Statistics	
Cronbach's Alpha	N of Items
.923	18

Meanwhile, of the 80 respondents, comprising active students in semesters 9, 11, and 13, as well as alumni who graduated beyond the 8th semester, 63.7% were female, while the remaining 36.3% were male. Active students made up 55% of the respondents, with the remaining 45% being alumni. When viewed from the year of admission, the majority of respondents were from the 2019 cohort, while the fewest were from the 2016 and 2018 cohorts. Among the 55% of active students, there

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were 27 ninth-semester students (61.4%), 9 eleventh-semester students (20.5%), and 8 thirteenth-semester students (18.2%).

3.2. Factor Analysis

Subsequently, the initial stage involved conducting the KMO and Bartlett tests. Based on Table 3, the KMO value is 0.898 with a Bartlett test of sphericity significance value of 0.000. According to theory, these variables are suitable for further analysis.

Table 3. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.898
Bartlett's Test of Sphericity	Approx. Chi-Square	1064.753
	df	153
	Sig.	.000

Meanwhile, the value of MSA for the 18 assessed variables from 80 respondents was above 0.5. Furthermore, Table 3 indicates that the largest contribution is made by variable X_{20} (supervisors and students collaborate to make research decisions) with a value of 0.925, meaning that 92.5% of the variance in variable X_{20} can be explained by the extracted factors. Conversely, the smallest contribution was made by variable X_{11} (students pursue a bachelor's degree for prestige and status) with a value of 0.406.

Table 4. Communalities Value

Variables	Initial	Extraction	Variables	Initial	Extraction
X_1	1.000	0.476	X_{20}	1.000	0.925
X_3	1.000	0.661	X_{21}	1.000	0.899
X_4	1.000	0.574	X_{22}	1.000	0.889
X_7	1.000	0.578	X_{23}	1.000	0.902
X_8	1,000	0.601	X_{24}	1.000	0.841
X_{10}	1.000	0.568	X_{25}	1.000	0.676
X_{11}	1.000	0.406	X_{26}	1.000	0.817
X_{14}	1.000	0.739	X_{27}	1.000	0.806
X_{16}	1.000	0.603			
X_{19}	1.000	0.411			
Extraction method: principal component analysis					

A total of 18 variables were included in the factor analysis. According to Table 5, only four factors could explain the 18 variables as these four factors had eigenvalues greater than 1.

Table 5. Factor Extraction Result with Principal Component Analysis

Total Variance Explained									
Component	*Initial Eigenvalues*			*Extraction Sums of Squared Loadings*			*Rotation Sums of Squared Loadings*		
	Total	*Variance (%)*	*Cumulative (%)*	*Total*	*Variance (%)*	*Cumulative (%)*	*Total*	*Variance (%)*	*Cumulative (%)*
1	7.815	43.417	43.417	7.815	43.417	43.417	6.557	36.430	36.430
2	2.241	12.453	55.870	2.241	12.453	55.870	2.065	11.471	47.901
3	1.217	6.764	62.634	1.217	6.764	62.634	1.931	10.730	58.631
4	1.098	6.100	68.734	1.098	6.100	68.734	1.818	10.103	68.734
5	0.990	5.501	74.235						
6	0.778	4.320	78.554						
7	0.734	4.079	82.634						
8	0.635	3.528	86.161						
9	0.590	3.276	89.438						
10	0.448	2.488	91.926						
11	0.414	2.302	94.228						

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Total Variance Explained									
Component	*Initial Eigenvalues*			*Extraction Sums of Squared Loadings*			*Rotation Sums of Squared Loadings*		
	Total	*Variance (%)*	*Cumulative (%)*	*Total*	*Variance (%)*	*Cumulative (%)*	*Total*	*Variance (%)*	*Cumulative (%)*
12	0.331	1.841	96.069						
13	0.200	1.114	97.183						
14	0.175	0.970	98.153						
15	0.128	0.712	98.865						
16	0.088	0.489	99.354						
17	0.070	0.386	99.740						
18	0.047	0.260	100.000						
Extraction Method: Principal Component Analysis.									

Table 5 shows that the four factors account for a cumulative variance of 68.73%. In other words, if the 18 variables are extracted into four factors, these four factors can explain 68.73% of the variation in the data, while the remaining 31.26% is explained by other factors not studied.

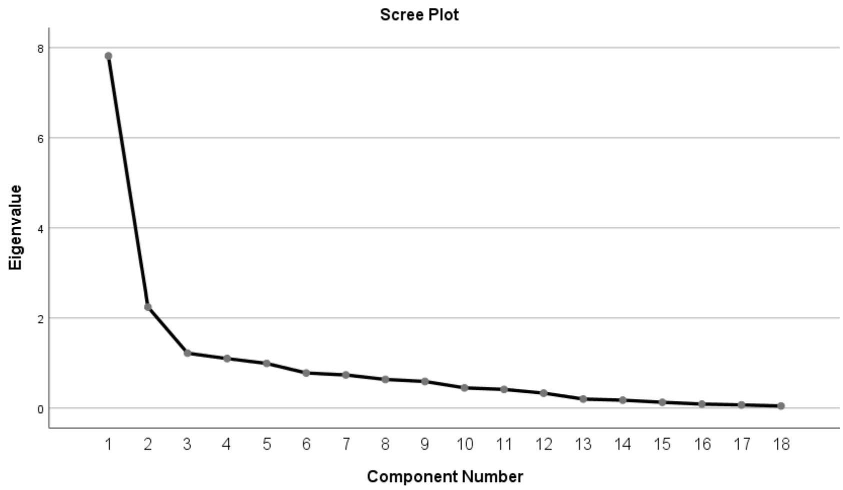

Fig. 1 Scree plot.

Fig. 1 shows the eigenvalue plot for each factor-forming variable. These results suggested that four factors were recommended to summarize the 18 variables. Meanwhile, from Table 3, four factors have been identified, but rotation was conducted to clarify the variables that form these factors. The rotated results can be seen in Table 6.

Table 6. Factor Loadings (Factor Weights) After Varimax Rotation

Rotated Component Matrix[a]				
	Component			
	1	*2*	*3*	*4*
X_1	0.067	0.662	0.172	0.054
X_3	0.148	0.725	0.111	0.318
X_4	0.196	0.731	0.035	-0.030
X_7	0.346	-0.002	0.676	0.037
X_8	0.060	0.329	0.694	0.089
X_{10}	0.225	0.103	0.704	0.103
X_{11}	0.048	0.125	-0.024	0.622
X_{14}	0.205	-0.030	0.069	0.831
X_{16}	0.021	0.269	0.409	0.602
X_{19}	0.203	0.440	0.173	0.383

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Rotated Component Matrix[a]				
	Component			
	1	*2*	*3*	*4*
X_{20}	0.919	0.197	0.116	0.168
X_{21}	0.923	0.147	0.052	0.154
X_{22}	0.913	0.161	0.041	0.170
X_{23}	0.924	0.152	0.136	0.073
X_{24}	0.878	0.098	0.244	0.017
X_{25}	0.756	0.138	0.292	-0.009
X_{26}	0.853	0.166	0.238	0.075
X_{27}	0.883	-0.010	0.114	0.117

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

According to Table 6, from the 18 variables, four factors could be formed, each of which can be interpreted as shown in Table 7.

Table 7. Variables Interpretation

No	Variables	Factor	Eigen Values	Loading Factors	Variance (%)	Cumulative (%)
1	X_{20}	The commitment of students and supervisors in completing the final project	7.815	0.919	43.417	4.417
2	X_{21}			0.923		
3	X_{22}			0.913		
4	X_{23}			0.924		
5	X_{24}			0.878		
6	X_{25}			0.756		
7	X_{26}			0.853		
8	X_{27}			0.883		
9	X_{1}	Factor campus and peer support	2.241	0.662	12.453	55.870
10	X_{3}			0.725		
11	X_{4}			0.731		
12	X_{19}			0.440		
13	X_{7}	Factor intelligence and discipline	1.217	0.676	6.764	62.634
14	X_{8}			0.694		
15	X_{10}			0.704		
16	X_{11}	Factor motivation and relation	1.098	0.622	6.100	68.734
17	X_{14}			0.831		
18	X_{16}			0.602		

Factor 1 consisted of variables such as supervisor-student collaboration in research decision-making (X_{20}), critical and constructive feedback from supervisors (X_{21}), supervisor's attention to student progress (X_{22}), optimal revision of final assignments by students (X_{23}), enjoyment of writing and researching by students (X_{24}), ease in determining thesis topics (X_{25}), easy access to research data (X_{26}), and proficiency in using the internet to find literature (X_{27}). This factor is called the student-supervisor commitment factor in completing final assignments. Factor 2 consisted of variables related to campus cleanliness (X_{1}), counseling and career support (X_{3}), availability of adequate library facilities (X_{4}), and social interaction among peers (X_{19}). This factor is called campus support and peer support. Factor 3 consisted of variables such as the availability of easily accessible administrative services (X_{7}), level of intelligence and talent (X_{8}), and student discipline level (X_{10}). This factor is referred to as the intelligence and discipline of students factor. Factor 4 comprised variables such as students pursuing a bachelor's degree for prestige and status (X_{11}), relationships with family members (X_{14}), and relationships between students and faculty members (X_{16}). This factor is called motivation and relationships.

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4. Conclusion

Four factors were identified to explain the 18 variables because they had eigenvalues above 1, with a cumulative variance of 68.734%. It means that if the 18 variables are extracted into four factors, these factors can explain 68.734% of the total variability of the original 18 variables without reducing the initial information from all variables. Therefore, it can be said that the factors influencing the delayed completion of studies among students in the Mathematics Program, FST, UNDANA, were student-supervisor commitment in completing final assignments, campus and peer support, intelligence and discipline, and motivation and relationships. Meanwhile, the most dominant factor affecting the delayed completion of studies among students in the Mathematics Program, FST, UNDANA, was factor 1, namely student-supervisor commitment in completing final assignments, accounting for 43.41% of the variance.

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