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A Two-Way Manova Analysis of Study Program and SchoolType on GPA and Study Duration

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Abstract

This study aimed to examine the effects of Study Program and Type of School as independent variables on students' academic achievement, measured by Grade Point Average (GPA) and Study Duration as dependent variables, at the Faculty of Science and Technology, UIN Sunan Kalijaga Yogyakarta. The study employed secondary academic data obtained from the faculty's Academic Office. The sample consisted of 210 undergraduate alumni from six study programs who graduated in May and August 2025. The data were analyzed using Two-Way Multivariate Analysis of Variance (Two-Way MANOVA), followed by Two-Way ANOVA, and post hoc tests using Tukey's Honest Significant Difference (HSD) and Estimated Marginal Means (EMMs). The results showed that Study Program had a significant effect on both GPA and Study Duration, while Type of School significantly influenced Study Duration but did not significantly affect GPA. In addition, the interaction between Study Program and Type of School significantly affected Study Duration. Post hoc analyses revealed that students from Informatics, Chemistry, and Industrial Engineering achieved significantly higher GPA than Physics students, whereas Biology students tended to have significantly longer study durations compared with several other study programs. Students from MA backgrounds also tended to require longer study duration than students from SMA backgrounds. These findings indicate that academic achievement in higher education is influenced more strongly by disciplinary characteristics than by prior school background alone. The study highlights the importance of curriculum evaluation, academic mentoring, and adaptive learning support systems to improve students' academic performance and timely graduation.

Keywords:GPA; Study Duration; Tukey's HSD Test; Two-Way MANOVA

INTRODUCTION

Higher education represents an advanced stage of formal education following secondary education, encompassing diploma, undergraduate, master's, specialist, and doctoral programs offered by universities (UU RI No. 20, 2003). Universities play a strategic role in producing high-quality human resources who are capable of adapting to the rapid development of science and technology. Within higher education, students' academic achievement is commonly reflected through two important indicators, namely Grade Point Average (GPA) and study duration. GPA represents students' academic performance and mastery of competencies, while study duration reflects the effectiveness and efficiency of the learning process. Students who complete their studies within the expected period and achieve satisfactory academic performance are often considered indicators of successful educational management and quality assurance within higher education institutions.

Previous studies have identified various factors influencing students' academic achievement, which can generally be classified into internal and external factors (Williams, 2010). Internal factors refer to characteristics inherent to students themselves, including motivation, self-regulation, learning styles, psychological conditions, learning interest, and academic engagement. Most existing studies have predominantly focused on these internal dimensions of learning (Awang et al., 2017) (Cetin, 2021) (Kamtsios, 2023) (Phipps & Amaya, 2023) (Richardson et al., 2012), emphasizing how psychological and behavioral aspects contribute to academic success. While these studies provide important insights into students' individual characteristics, research examining external educational factors remains relatively limited, particularly studies investigating how school background and study program influence students' academic achievement in higher education.

In the context of higher education, external factors are important because they are associated with students' prior educational experiences, institutional environments, and academic adaptation processes. Differences in school background may shape students' readiness to face university learning systems, analytical abilities, independent learning skills, and academic habits. Students graduating from general senior high schools (SMA), vocational schools (SMK), Islamic senior high schools (MA), or Islamic boarding schools may possess different educational experiences due to variations in curriculum orientation, instructional methods, and academic emphasis. These differences may subsequently influence students' academic performance and their ability to complete their studies within the expected timeframe.

Likewise, differences in study programs may also contribute to variations in academic achievement because each discipline has distinct curriculum structures, competency demands, levels of difficulty, and learning approaches. Programs within the pure sciences generally require strong theoretical and quantitative competencies, whereas applied or interdisciplinary programs may emphasize practical, technological, and project-based learning. Consequently, students may experience different academic pressures and learning challenges depending on the study program in which they are enrolled.

Although universities generally implement standardized admission systems and minimum selection criteria to ensure the quality of incoming students, such standardization does not necessarily eliminate heterogeneity among students. Admission processes mainly function as an initial screening mechanism and may not fully capture differences in educational background, learning culture, academic adaptation, and long-term academic performance. Students who meet similar admission standards may still demonstrate different academic outcomes because of disparities in prior educational experiences and disciplinary contexts. Therefore, investigating the influence of school background and study program on academic achievement remains relevant, particularly in understanding whether these external factors continue to affect GPA and study duration after students enter higher education.

Several previous studies have employed Multivariate Analysis of Variance (MANOVA) to investigate educational outcomes involving multiple dependent variables simultaneously (Inamete et al., 2020) (Nyame et al., 2018) (Okeke et al., 2018) (Retutas & Rubio, 2021) (Udokang et al., 2021). MANOVA is a statistical technique designed to examine simultaneous differences across two or more dependent variables influenced by one or more independent variables (Hair et al., 2019) (Johnson & Wichern, 2007) (Mertler & Vannatta Reinhart, 2016). This method is particularly advantageous because it allows researchers to evaluate the combined effects of independent variables while considering correlations among dependent variables. Previous studies generally conclude that MANOVA is an effective and robust approach for analyzing educational phenomena involving multiple academic outcomes. However, despite the increasing application of MANOVA in educational research, studies simultaneously examining GPA and study duration as dependent variables in relation to school background and study program remain scarce, particularly in the context of Islamic higher education institutions in Indonesia.

The Faculty of Science and Technology (FST) at UIN Sunan Kalijaga Yogyakarta provides an appropriate context for examining these issues because it accommodates students from diverse educational backgrounds and study programs. Students at FST originate from general senior high schools (SMA), vocational schools (SMK), Islamic senior high schools (MA), Islamic boarding schools, and other educational pathways, each characterized by different curricula and instructional approaches. In addition, FST consists of various study programs such as Mathematics, Biology, Physics, Chemistry, Industrial Engineering, and Informatics, which differ in curriculum structure, academic workload, and competency orientation. These variations potentially contribute to differences in students' academic achievement, both in terms of GPA and study duration.

Based on these considerations, this study aims to investigate the influence of school background and study program on students' GPA and study duration using Two-Way Multivariate Analysis of Variance (Two-Way MANOVA) at the Faculty of Science and Technology, UIN Sunan Kalijaga Yogyakarta. This study is expected to contribute to the existing literature by providing empirical evidence regarding the role of external educational factors in shaping academic achievement within higher education. Furthermore, the findings are expected to provide valuable input for universities and faculties in developing admission policies, curriculum design, academic support systems, and learning strategies aimed at improving students' academic success and study completion.

RESEARCH METHODS

Data Collection

This study employed a quantitative research design using a causal-comparative approach to investigate the influence of school background and study program on students' academic achievement. The research utilized secondary data obtained from the Academic Office of the Faculty of Science and Technology (FST), UIN Sunan Kalijaga Yogyakarta. The data consisted of academic records of undergraduate (S1) alumni who graduated in May and August 2025. These graduation periods were selected to ensure data recency and representation across all study programs within the faculty.

The population of this study comprised all undergraduate alumni of the Faculty of Science and Technology who graduated in 2025. The sampling technique used was total sampling, in which all alumni meeting the research criteria were included in the analysis. This approach was chosen to provide comprehensive representation of graduates from different educational backgrounds and study programs. The sample used in this study consisted of 210 undergraduate students from six study programs within the Faculty of Science and Technology, UIN Sunan Kalijaga Yogyakarta, namely Biology, Physics, Chemistry, Mathematics, Informatics, and Industrial Engineering.

Variabel of Research

This study involved two dependent variables and two independent variables. The dependent variables were Grade Point Average (GPA) and Study Duration. GPA was measured on a ratio scale ranging from 0 to 4, while Study Duration was measured in years, calculated from the student's initial enrolment until graduation. The independent variables were Type of School and Study Program. Type of School was categorized into General Senior High School (SMA), Vocational High School (SMK), Islamic Senior High School (MA), and Others. Meanwhile, Study Program consisted of Biology, Physics, Chemistry, Mathematics, Informatics, and Industrial Engineering. The detailed operational definitions of the research variables are presented in Table 1.

Table 1: Research Variables

Variable	**Type of Data**	**Description**
Y_1 = GPA	Ratio	$0 \leq GPA \leq 4$
Y_2 = Study Duration	Ratio	Measured in years
X_1 = Type of School	Categorical	General Senior High School (SMA)
		Vocational High School (SMK)
		Islamic Senior High School (MA)
		Others
X_2 = Study Program	Categorical	Biology
		Physics
		Chemistry
		Mathematics
		Informatics
		Industrial Engineering

The data were analyzed using Two-Way Multivariate Analysis of Variance (Two-Way MANOVA). This method was selected because the study involved two dependent variables analyzed simultaneously with two categorical independent variables. Two-Way MANOVA enables the examination of the main effects of Type of School and Study Program, as well as their interaction effect on GPA and Study Duration simultaneously.

Two-Way MANOVA

The Two-Way MANOVA is an extension of the Multivariate Analysis of Variance (MANOVA) that simultaneously involves two independent factors. The concept of this model is to assess whether groups defined by the combination of these two factors differ significantly across multiple dependent variables. Specifically, this procedure allows for testing: (1) the main effect of the first factor on the dependent variables, (2) the main effect of the second factor, and (3) the interaction effect between the two factors, which indicates whether the influence of one factor depends on the level of the other (Hair et al., 2019), (Johnson & Wichern, 2007), (Mertler & Vannatta Reinhart, 2016).

The model of the Two-Way Multivariate Analysis of Variance (MANOVA) is formulated as follows (Johnson & Wichern, 2007):

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \varepsilon_{ijk} \tag{1}$$

With: $i = 1, 2, \ldots, a;\ j = 1, 2, \ldots, b;\ k = 1, 2, \ldots, n$

Where: $\sum_{i=1}^{a} \alpha_i = 0, \quad \sum_{j=1}^{b} \beta_j = 0, \quad \sum_{i=1}^{a} (\alpha\beta)_{ij} = 0, \quad \sum_{j=1}^{b} (\alpha\beta)_{ij} = 0$

y_{ijk} =vector of dependent variables for the k^{th} observation in the i^{th} level of factor A and the j^{th} level of factor B

μ = vector of overall means

α_i = effect of the i^{th} level of factor A, $i = 1, 2, \ldots, a$

β_j = effect of the j^{th} level of factor B, $j = 1, 2, \ldots, b$

$(\alpha\beta)_{ij}$ = interaction effect between factors A and B

ε_{ijk} = vector of random error terms assumed to follow a multivariate normal distribution with mean zero and covariance matrix Σ $(\varepsilon_{ijk} \sim N(\mathbf{0}, \Sigma))$

The hypothesis testing in Two-Way MANOVA aims to determine whether there are significant differences in the vector of dependent variables across the levels of each factor and their interaction. The hypotheses can be formulated as follows:

1. **Main effect of Factor A**
   $H_0 : \mu_{1.} = \mu_{2.} = \cdots = \mu_{a.}$
   H_1 : At least one μ_i differs
   This hypothesis tests whether there are significant differences in the vector of dependent variables among the levels of Factor A.

2. **Main effect of Factor B**
   $H_0 : \mu_{.1} = \mu_{.2} = \cdots = \mu_{.b}$
   H_1 : At least one μ_i differs
   This tests whether the mean vectors of the dependent variables differ across the levels of Factor B.

3. **Interaction effect between Factors A and B**
   $H_0 : \mu_{(AB)ij} = 0, \quad \forall i, j$
   H_1 : At least one $\mu_{(AB)ij} \neq 0, \quad \forall i, j$
   This hypothesis tests whether the effect of one factor on the dependent variables depends on the level of the other factor

Table 2: Summary of Two-Way MANOVA Results

Source of Variance	Matrix of Sum of Squares and Cross Products	Degree of Freedom
Factor A	$\mathbf{H}_A = \sum_{i=1}^{a} bn\left(\bar{\mathbf{y}}_{i\cdot} - \bar{\mathbf{y}}\right)\left(\bar{\mathbf{y}}_{i\cdot} - \bar{\mathbf{y}}\right)'$	$a-1$
Factor B	$\mathbf{H}_B = \sum_{j=1}^{b} an\left(\bar{\mathbf{y}}_{\cdot j} - \bar{\mathbf{y}}\right)\left(\bar{\mathbf{y}}_{\cdot j} - \bar{\mathbf{y}}\right)'$	$b-1$
Interaction (AB)	$\mathbf{H}_{AB} = \sum_{i=1}^{a}\sum_{j=1}^{b} n\left(\bar{\mathbf{y}}_{ij} - \bar{\mathbf{y}}_{i\cdot} - \bar{\mathbf{y}}_{\cdot j} + \bar{\mathbf{y}}\right)\left(\bar{\mathbf{y}}_{ij} - \bar{\mathbf{y}}_{i\cdot} - \bar{\mathbf{y}}_{\cdot j} + \bar{\mathbf{y}}\right)'$	$(a-1)(b-1)$
Error	$\mathbf{E} = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{n}\left(\mathbf{y}_{ijk} - \bar{\mathbf{y}}_{ij}\right)\left(\mathbf{y}_{ijk} - \bar{\mathbf{y}}_{ij}\right)'$	$ab(n-1)$
Total	$\mathbf{T} = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{n}\left(\mathbf{y}_{ijk} - \bar{\mathbf{y}}\right)\left(\mathbf{y}_{ijk} - \bar{\mathbf{y}}\right)'$	$abn-1$

In the Two-Way MANOVA, several multivariate test statistics can be used to evaluate the significance of the main and interaction effects. These statistics assess whether the population mean vectors of the dependent variables differ across the levels of the independent factors. The most commonly used test statistics are Wilks' Lambda, Pillai's Trace, Hotelling's Trace, and Roy's Largest Root. Each provides a slightly different emphasis on how variance is partitioned across groups, yet they often yield similar conclusions when assumptions are met (Hair et al., 2019), (Johnson & Wichern, 2007).

1. **Wilks' Lambda (Λ)**

$$\Lambda = \frac{|E|}{|E+H|} \tag{2}$$

   where E is the error (within-group) sum of squares and cross-products matrix, and H is the hypothesis (between-group) sum of squares and cross-products matrix.

2. **Pillai's Trace (V)**

$$V = trace\left[H(H+E)^{-1}\right] = \sum_{i=1}^{s} \frac{\lambda_i}{1+\lambda_i} \tag{3}$$

   where λ_i is the eigen value of matrix $(HE)^{-1}$; $s = \min(p, df_{effect})$ and p = number of dependent variables. Pillai's Trace is considered the most robust statistic, especially when assumptions of equality of covariance matrices or multivariate normality are mildly violated.

3. **Hotelling's Trace (T^2)**

$$T^2 = \mathrm{trace}\left((HE)^{-1}\right) = \sum_{i=1}^{s} \lambda_i \tag{4}$$

   This statistic emphasizes the sum of the latent roots (eigenvalues) of $E^{-1}H$, giving more weight to the dimensions with stronger effects.

4. **Roy's Largest Root (Θ)**

$$\Theta = \lambda_{\max} \tag{5}$$

   $\lambda_{\max}$ is the largest eigen value of the matrix $(HE)^{-1}$. Roy's test focuses only on the single largest root (dimension) that explains the greatest variance between groups.

Although all four tests may be used, Pillai's Trace is generally preferred when sample sizes are unequal or assumptions are slightly violated, due to its higher robustness. Before conducting the MANOVA analysis, several statistical assumptions were tested to ensure the validity of the model. First, multivariate normality was assessed using the Henze–Zirkler test. Second, homogeneity of variance-covariance matrices among groups was evaluated using Box's M test. Third, homogeneity of variances for each dependent variable was examined using Levene's test. In addition, multicollinearity between dependent variables was assessed through correlation analysis to ensure that the dependent variables were moderately correlated but not excessively collinear. Observations were also assumed to be independent because each student represented a separate observational unit. The hypotheses in this study were tested at a significance level of 5% $(\alpha = 0.05)$. If the MANOVA results indicated significant effects, follow-up univariate ANOVA tests were conducted to identify which dependent variables contributed to the multivariate differences. All statistical analyses were

RESULT AND DISCUSSION

Descriptive Analysis

The sample used in this study consisted of 210 undergraduate students from six study programs within the Faculty of Science and Technology, UIN Sunan Kalijaga. The descriptive characteristics of the respondents based on gender, age, type of school, and study program are presented in the following table:

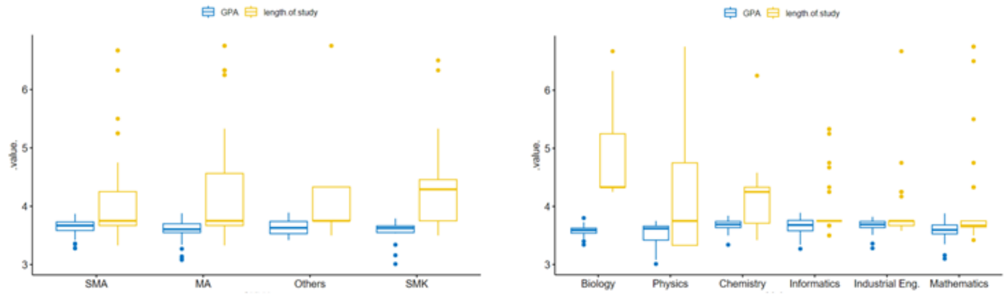
Table 3: Characteristics of Respondents by Gender, Age, Type of School, and Study Program

Variable	Category	Frequency	Percentage (%)
Gender	Male	75	35.71
	Female	135	64.29
Age	20–21 years	44	20.95
	22–23 years	142	67.62
	24–25 years	22	10.48
	26–27 years	2	0.95
Type of School	General Senior High School (SMA)	122	58.10
	Vocational High School (SMK)	13	6.19
	Islamic Senior High School (MA)	62	29.52
	Others	13	6.19
Study Program	Biology	27	12.86
	Physics	19	9.05
	Chemistry	31	14.76
	Mathematics	44	20.95
	Informatics	52	24.76
	Industrial Engineering	37	17.62

Based on Table 3, the characteristics of the respondents show that the majority were female, totalling 135 individuals (64.29%), while male respondents accounted for 75 individuals (35.71%). In terms of age, most respondents were between 22–23 years old, comprising 142 individuals (67.62%), followed by those aged 20–21 years (44 individuals or 20.95%), 24–25 years (22 individuals or 10.48%), and only a small number aged 26–27 years (2 individuals or 0.95

Regarding educational background, most respondents graduated from General Senior High School (SMA), with 122 individuals (58.10%), followed by those from Islamic Senior High School (MA) with 62 individuals (29.52%), and both Vocational High School (SMK) and other school types with 13 individuals each (6.19%). In terms of study program, the largest proportion of respondents came from Industrial Engineering (24.76%) and Mathematics (20.95%), while the smallest proportion was from Physics (9.05%).These findings indicate that the sample was dominated by female respondents aged around 22–23 years, most of whom graduated from SMA.

At this stage, a descriptive analysis was conducted using boxplots. Boxplots provide a visual representation of data distribution, including the median, interquartile range, and the degree of variation across groups (Frigge et al., 1989). Through boxplots, comparisons between groups—such as school background or study program—can be more easily and clearly observed. The use of boxplots not only presents a concise summary of data distribution but also supports preliminary interpretation before conducting the Two-Way MANOVA test.



(a). Type of School (b). Study Program

Figure 1: (a) Boxplot of GPA and Study Duration variables based on Type of School and (b) Boxplot of GPA and Study Duration variables based on Study Program

Figure 1a presents a comparison of GPA (blue) and study duration (yellow) based on students' high school backgrounds (SMA, MA, SMK, and others). GPA remains relatively consistent across all groups, with medians between 3.5 and 3.7 and a narrow interquartile range, indicating low variability. In contrast, study duration varies more widely, reflecting noticeable differences in time to graduation among high school groups.

Figure 1b shows boxplots of GPA (blue) and study duration (yellow) across study programs (Biology, Physics, Chemistry, Mathematics, Informatics, and Industrial Engineering). GPA is generally stable across programs, with medians ranging from 3.4 to 3.7, though some outliers appear in Physics, Informatics, and Mathematics. Study duration exhibits greater variability, especially in Physics and Biology, which show higher medians and wider interquartile ranges, with a few students taking over six years to graduate. Conversely, Informatics, Industrial Engineering, and Mathematics display lower median durations and narrower variation, indicating faster and more consistent study completion.

Assumption Testing for Two-Way MANOVA

Two-Way MANOVA requires several key assumptions: multivariate normality within each group combination, homogeneity of covariance matrices across groups, and independent observations. If normality or homogeneity assumptions are violated, more robust statistics such as Pillai's Trace can be used to ensure valid results.

Homogeneity Test

The equality of variance–covariance matrices was assessed using Box's M-test with the following hypotheses:

- H_0 : The variance–covariance matrices are equal (homogeneous) across groups,
- H_1 : The variance–covariance matrices are not equal (heterogeneous) across groups.

The results are summarizaed in the table below:

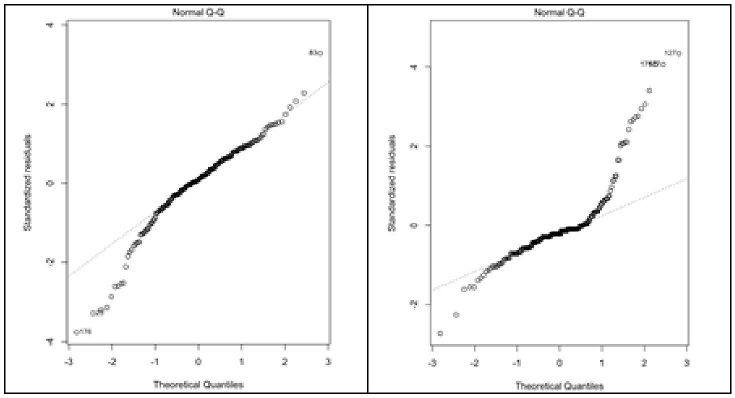
Table 4: Results of the Homogeneity Test Using Box's M-test

Variable	**Chi-Square (Approx.)**	**df**	**p-value**
Study Program	61.781	15	1.243×10^{-7}
Type of School	31.919	9	0.0002056

The Box's M-test for the homogeneity of covariance matrices showed significant results for both Study Program $(X^2 = 61.781; df = 15; p < 0.001)$ and Study Duration $(X^2 = 31.919; df = 9; p < 0.001)$, indicating that the homogeneity assumption was violated. Despite this, robust statistics such as Pillai's Trace were employed to ensure the validity of the MANOVA results.

Multivariate Normality Test

Multivariate normality of the dependent variables was evaluated using Q-Q plots of the residuals. Q-Q plots provide a visual assessment of whether the residuals follow a multivariate normal distribution, offering a more comprehensive evaluation than purely statistical tests such as MShapiro test.



(a) Study Program (b). Type of School

Figure 2: ((a). Normal Q-Q Plot for Study Program, (b) Normal Q-Q Plot for School Origin

Figure 2 presents Q-Q plots for (a) Study Program and (b) High School Background. Most points closely follow the diagonal line (theoretical quantiles), indicating that the residuals are approximately normally distributed. Some deviations at the upper-right and lower-left tails reflect outliers with large residuals, suggesting minor departures from normality in the extremes. Overall, the data sufficiently meet the multivariate normality assumption, allowing the MANOVA analysis to proceed.

Two-Way MANOVA Analysis

In this study, the effects of Study Program and Type of School on GPA and Study Duration were analyzed using the Two-Way MANOVA method. Based on the assumption tests, it was found that the homogeneity and normality assumptions were not fully met. Therefore, the more robust Pillai's Trace statistic was employed, as it is relatively stable and less sensitive to assumption violations compared to other multivariate test statistics. The results of the Two-Way MANOVA are presented in the table below.

Table 5: Results of the Two-Way MANOVA

	Df	Pillai	approx F	Num Df	Den Df	Pr(>F)
Study Program	5	0.4116	9.6396	10	372	$2.502e^{-14}$ ***
Type of School	3	0.0622	1.99	6	372	0.066216.
Study Program: Type of School	15	0.2586	1.8418	30	372	0.005332 **
Residuals	186					
Signif. codes:	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'	0.1 ' '	

The results of the Two-Way MANOVA indicated that the Study Program factor had a significant effect on both Study Duration and GPA (Pillai's Trace = 0.4116; $F = 9.6396$; $p < 0.001$), suggesting differences in Study Duration and GPA across programs.

In contrast, the Type of School factor yielded a Pillai's Trace value of 0.0622, with an approximate F of 1.99 and $p = 0.066216$. This result was not significant at the 5% level, although it approached significance at the 10% level, indicating that pre-university educational background does not directly affect Study Duration and GPA.

However, the interaction between Study Program and Type of School was significant (Pillai's Trace = 0.2586; $F = 1.8418$; $p = 0.0053$), implying that the effect of Type of School on Study Duration and GPA varies depending on the program enrolled.

Tw-Way ANOVA and Post Hoc Test Analysis for GPA

Two-Way Analysis of Variance (Two-Way ANOVA) is a statistical method used to examine the effects of two independent categorical variables (factors) on a single continuous dependent variable simultaneously. Two-Way ANOVA was used to examine the effects of Study Program and Type of School on students' GPA and Study Duration.

Table 6: Results of the Two-Way ANOVA for GPA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Study Program	5	0.6142	0.122839	6.8669	$6.634e^{-06}$ ***
Type of School	3	0.1351	0.045043	2.5180	0.05954.
Study Program: Type of School	15	0.4162	0.027750	1.5513	0.09123.
Residuals	186	3.3273	0.017889		
Signif. codes:	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'	0.1 ' '

Based on the results presented in Table 6, the Study Program factor had a statistically significant effect on GPA $(F = 6.867, p < 0.001)$. This finding indicates that students' GPA differed significantly across study programs suggesting that disciplinary characteristics such as curriculum structure, academic workload, learning methods, and competency demands contributed to differences in academic performance. Meanwhile, Type of School did not show a statistically significant effect on GPA at the 5% significance level $(F = 2.518, p = 0.059)$. This finding suggests that students from different school types, including SMA, SMK, MA, and others, were generally able to adapt similarly to the university academic environment.

In addition, the interaction between Study Program and Type of School was not statistically significant $(F = 1.551, p = 0.091)$. This result indicates that the effect of school background on GPA did not differ substantially across study programs. Consequently, the influence of study program appears to be more dominant than prior school background in determining students' GPA outcomes.

To evaluate the magnitude of the observed effects, partial eta squared (partial η^2) was reported as a measure of effect size. In MANOVA, partial η^2 represents the proportion of variance in the dependent variables that is attributable to an independent variable after controlling for other variables included in the model (Olejnik & Algina, 2003); (Steiger, 2004). The values of partial η^2 range from 0 to 1, where values closer to 0 indicate weaker effects and values closer to 1 indicate stronger effects. Accordingly, larger partial η^2 values reflect greater practical significance of the independent variable in explaining variations in the dependent variables. Following Cohen's guideline (Cohen, 1988), partial η^2 values of $0.01, 0.06,$ and 0.14 are generally interpreted as small, medium, and large effect sizes, respectively.

Table 7: Effect Size Results for GPA Based on Partial Eta Squared (η^2)

	Eta2 (partial)	**95% CI**	**Interpretation**
Study Program	0.16	[0.07, 1.00]	Medium
Type of School	0.04	[0.00, 1.00]	Small
Study Program : Type of School	0.11	[0.00, 1.00]	Small

The effect size analysis presented in Table 7 indicates that Study Program had the largest contribution to variations in students' GPA, with a partial η^2 value of 0.16, which falls within the medium effect category according to Cohen's guideline. The result is consistent with the Two-Way Anova analysis, which demonstrated that Study Program had statistically significant effect on GPA.

Meanwhile, Type of School showed a relatively small effect on GPA, with a partial η^2 value of 0.04. This result indicates that students' prior educational background contributed only slightly to GPA variation, suggesting that students from different school types were generally able to adapt similarly to the university learning environment.

The interaction between Study Program and Type of School produced a partial η^2 value of 0.11, categorized as a small effect. This indicates that the influence of school background on GPA varied slightly across study programs, although the interaction effect was not substantial.

To further examine the significant effect of Study Program on GPA identified in the Two-Way ANOVA, a post hoc analysis was conducted using Tukey's Honest Significant Difference (HSD) test. The results are presented in Table 8.

Table 8: Post Hoc Test Results for GPA Based on Study Program Using Tukey's HSD Test

	diff	**lower**	**upper**	**p-adj**	**Significance**
Mathematics–Physics	0.0733	-0.0325	0.1790	0.3487	Not Significant
Biology–Physics	0.0733	-0.0420	0.1886	0.4491	Not Significant
Informatics–Physics	0.1495	0.0408	0.2582	0.0015	Significant
Chemistry–Physics	0.1629	0.0506	0.2751	0.0006	Significant
Industrial Eng.–Physics	0.1639	0.0607	0.2672	0.0001	Significant
Biology–Mathematics	0.0000	-0.0941	0.0942	1.0000	Not Significant
Informatics–Mathematics	0.0763	-0.0097	0.1622	0.1137	Not Significant
Chemistry–Mathematics	0.0896	-0.0007	0.1799	0.0533	Not Significant
Industrial Eng.–Mathematics	0.0906	0.0117	0.1695	0.0142	Significant
Informatics–Biology	0.0762	-0.0212	0.1737	0.2194	Not Significant
Chemistry–Biology	0.0896	-0.0118	0.1909	0.1170	Not Significant
Industrial Eng.–Biology	0.0906	-0.0007	0.1820	0.0533	Not Significant
Chemistry–Informatics	0.0133	-0.0805	0.1071	0.9985	Not Significant
Industrial Eng.–Informatics	0.0144	-0.0685	0.0972	0.9961	Not Significant
Industrial Eng.–Chemistry	0.0011	-0.0863	0.0884	1.0000	Not Significant

The post hoc analysis showed several significant differences in GPA among study programs. Students from Informatics, Chemistry, and Industrial Engineering had significantly higher GPA scores compared with students from Physics, with adjusted p-values of $0.0015, 0.0006,$ and $0.0001,$ respectively. In addition, Industrial Engineering students also demonstrated significantly higher GPA than Mathematics students $(p = 0.0142)$.

Meanwhile, the remaining comparisons among study programs were not statistically significant, indicating relatively similar GPA performance across those groups. Overall, the significant differences mainly involved the Physics study program, which tended to show lower GPA outcomes compared with several other disciplines.

The results of the Two-Way ANOVA and post hoc analyses indicate that students' academic achievement, measured by GPA, was influenced more strongly by Study Program than by Type of School. This finding suggests that academic performance in higher education is primarily shaped by differences in curriculum characteristics, academic workload, teaching methods, and competency demands within each discipline rather than by students' prior educational backgrounds.

The post hoc analysis further revealed that students from Informatics, Chemistry, and Industrial Engineering achieved significantly higher GPA scores compared with students from Physics. Educationally, this finding may indicate that students in Physics face greater academic challenges due to the intensive theoretical, mathematical, and analytical nature of the curriculum. In contrast, programs such as Informatics and Industrial Engineering may provide more applied and structured learning approaches that support students' academic achievement more effectively.

Meanwhile, the absence of a significant effect of Type of School suggests that students from SMA, SMK, MA, and other school backgrounds were generally able to adapt similarly to the university learning environment. This finding reflects that the academic system at the Faculty of Science and Technology may have successfully provided relatively equal learning opportunities for students regardless of their educational background.

Overall, these results imply that improving educational quality should focus more on strengthening internal academic processes within study programs, such as curriculum evaluation, academic mentoring, learning support systems, and teaching strategies, particularly in programs with relatively lower GPA performance.

Two-Way ANOVA and Post Hoc Test Analysis for Study Duration

The results of the Two-Way ANOVA for Study Duration are presented in Table 9

Table 9: Results of the Two-Way ANOVA for Study Duration

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Study Program	5	19.122	3.8245	8.5657	$2.547e-07$***
Type of School	3	5.227	1.7422	3.9020	0.009826**
Study Program $\times$ Type of School	15	12.860	0.8573	1.9202	0.023549*
Residuals	186	83.047	0.4465		
Significance codes :	$0'***'$	$0,001'**'$	$0,01'*'$	$0,05'.'$	$0,1''$

Based on the results presented in Table 9, Study Program had a highly significant effect on Study Duration $(F = 8.566, p < 0.001)$. This finding indicates that the length of time required to complete undergraduate studies differed significantly across study programs. Type of School also showed a statistically significant effect on Study Duration $(F = 3.902, p = 0.0098)$. This result indicates that students' educational background influenced the duration of their studies at the university level. Students from different school types, such as SMA, SMK, MA, and others, may possess different levels of academic readiness, learning habits, and adaptation skills that affect their ability to complete higher education within the expected timeframe.

Furthermore, the interaction between Study Program and Type of School was statistically significant $(F = 1.920, p = 0.0235)$. This finding indicates that the effect of Study Program on Study Duration varied depending on students' school backgrounds. In other words, students from certain educational backgrounds may experience different levels of difficulty or adaptation across specific study programs. This interaction suggests that the relationship between educational background and academic progression is not uniform across disciplines.

Table 10: Effect Size Results for Study Duration Based on Partial Eta Squared (partialη^2)

	Eta2 (partial)	95% CI	Interpretation
Study Program	0.19	[0.07, 1.00]	Medium
Type of School	0.06	[0.00, 1.00]	Small
Study Program : Type of School	0.13	[0.00, 1.00]	Medium

The effect size analysis presented in Table 10 strengthens the findings of the Two-Way ANOVA results in Table 9. The ANOVA analysis showed that Study Program had a highly significant effect on Study Duration $(F = 8.566, p < 0.001)$, and this result was supported by the partial eta squared value of 0.19, which falls within the medium effect category according to Cohen's guideline. This indicates that approximately 19% of the variance in students' study duration can be explained by differences among study programs after controlling for other variables in the model.

Furthermore, the ANOVA results revealed that Type of School significantly affected Study Duration $(F = 3.902, p = 0.0098)$. However, the effect size analysis showed a relatively smaller contribution, with a partial η^2 value of 0.06, categorized as a small effect. This finding suggests that although students' educational backgrounds significantly influenced study duration statistically, the practical magnitude of the effect was relatively limited compared with Study Program.

In addition, the interaction between Study Program and Type of School was statistically significant in the ANOVA analysis $(F = 1.920, p = 0.0235)$, and the corresponding partial η^2 value of 0.13 indicated a moderate effect size. This result suggests that the influence of educational background on study duration differed across study programs and contributed meaningfully to variations in graduation time. In certain disciplines, students from particular school backgrounds may adapt more effectively and complete their studies faster than others. The moderate interaction effect indicates that the compatibility between students' prior educational experiences and the academic characteristics of specific study programs may influence study completion patterns.

Because the Two-Way ANOVA results indicated that Study Duration had a statistically significant, a post hoc analysis was conducted using Tukey's Honest Significant Difference (HSD) test.

Table 11: Post Hoc Test Results for Study Duration Based on Study Program Using Tukey's HSD Test

	diff	**lower**	**upper**	**p-adj**	**Significance**
Mathematics–Industrial Eng.	0.1329	-0.2613	0.5270	0.9266	Not Significant
Informatics–Industrial Eng.	0.1561	-0.2578	0.5699	0.8865	Not Significant
Chemistry–Industrial Eng.	0.3569	-0.0797	0.7935	0.1783	Not Significant
Physics–Industrial Eng.	0.4291	-0.0867	0.9449	0.1631	Not Significant
Biology–Industrial Eng.	0.9721	0.5157	1.4285	0.0000	Significant
Informatics–Mathematics	0.0232	-0.4060	0.4524	1.0000	Not Significant
Chemistry–Mathematics	0.2240	-0.2272	0.6752	0.7089	Not Significant
Physics–Mathematics	0.2962	-0.2320	0.8245	0.5897	Not Significant
Biology–Mathematics	0.8392	0.3688	1.3096	0.0000	Significant
Chemistry–Informatics	0.2008	-0.2677	0.6693	0.8194	Not Significant
Physics–Informatics	0.2730	-0.2700	0.8161	0.6977	Not Significant
Biology–Informatics	0.8160	0.3290	1.3031	0.0000	Significant
Physics–Chemistry	0.0722	-0.4884	0.6328	0.9991	Not Significant
Biology–Chemistry	0.6152	0.1087	1.1217	0.0076	Significant
Biology–Physics	0.5430	-0.0332	1.1192	0.0773	Not Significant

The Tukey HSD post hoc test results in Table 11 indicate that significant differences in Study Duration were mainly found between the Biology study program and several other programs. Biology students had significantly longer study durations compared with students in Industrial Engineering $(p < 0.001)$, Mathematics $(p < 0.001)$, Informatics $(p < 0.001)$, and Chemistry $(p = 0.0076)$. The largest difference was observed between Biology and Industrial Engineering $(diff = 0.9721)$.

Meanwhile, no significant differences were found among Mathematics, Informatics, Chemistry, Physics, and Industrial Engineering, indicating relatively similar study completion patterns across these programs. These findings support the ANOVA results in Table 8, which showed that Study Program significantly affected Study Duration.

Table 12: Post Hoc Test Results for Study Duration Based on Type of School Using Tukey's HSD Test

	diff	**lower**	**upper**	**p-adj**	**Significance**
Others–SMA	0.0691	-0.4361	0.5743	0.9847	Not Significant
MA–SMA	0.2730	0.0002	0.5458	0.0497	Significant
SMK–SMA	0.4721	-0.0165	0.9607	0.0624	Not Significant
MA–Others	0.2039	-0.3260	0.7339	0.7509	Not Significant
SMK–Others	0.4030	-0.2642	1.0702	0.4006	Not Significant
SMK–MA	0.1991	-0.3151	0.7132	0.7474	Not Significant

The Tukey HSD post hoc test results in Table 12 indicate that a significant difference in Study Duration was found only between students from Islamic Senior High Schools (MA) and General Senior High Schools (SMA) $(p = 0.0497)$. Students from MA backgrounds tended to have longer study durations compared with students from SMA backgrounds, with a mean difference of 0.2730 years.

Meanwhile, no significant differences were observed among the other school background comparisons, including SMA, SMK, and Others. These findings suggest that although Type of School significantly affected Study Duration in the ANOVA results (Table 9), the differences were generally limited across most school categories.

To further examine the significant interaction effect between Study Program and Type of School identified in the Two-Way ANOVA, a post hoc analysis was conducted using the Estimated Marginal Means (EMMs) comparison with Tukey adjustment. This test was performed to identify which specific combinations of Study Program and Type of School differed significantly in Study Duration. Table 13 presents only the statistically significant comparison results. Overall, there were 16 significant differences identified among the interaction groups.

The post hoc results revealed several significant differences across group combinations. Students from the Biology program with MA backgrounds showed significantly longer study durations compared with students from Industrial Engineering, Informatics, Mathematics, and Physics with SMA backgrounds $(p < 0.05)$.

In addition, students from the Physics program with "Others" school backgrounds differed significantly from several SMA groups, including Chemistry, Industrial Engineering, Informatics, Mathematics, and Physics itself. The largest difference was observed between Physics–Others and Physics–SMA, with an estimated mean difference of 3.0545 years.

Furthermore, Biology students from SMA backgrounds also demonstrated significantly longer study durations compared with Industrial Engineering and Mathematics students from SMA backgrounds.

Table 13: Post Hoc Test Results for Interaction Effect between Study Program and Type of School Based on Estimated Marginal Means

Contrast	Estimate	SE	df	t.ratio	p-value
Biology MA – Industrial Eng. SMA	1.1787	0.2281	186	5.1671	0.0002
Biology MA – Informatics SMA	1.0541	0.2467	186	4.2719	0.0067
Biology MA – Mathematics SMA	1.2278	0.2450	186	5.0125	0.0156
Biology MA – Physics SMA	1.2945	0.2849	186	4.5435	0.0003
Industrial Eng. MA – Physics Others	-2.7800	0.7087	186	-3.9225	0.0023
Informatics MA – Physics Others	-2.7250	0.7008	186	-3.8883	0.0183
Mathematics MA – Physics Others	-2.6213	0.6901	186	-3.7984	0.0309
Industrial Eng. Others – Physics Others	-3.0200	0.7471	186	-4.0425	0.0051
Informatics Others – Physics Others	-3.0833	0.7716	186	-3.9962	0.0118
Physics Others – Chemistry SMA	2.6463	0.6888	186	3.8420	0.0045
Physics Others – Industrial Eng. SMA	2.9387	0.6767	186	4.3426	0.0045
Physics Others – Informatics SMA	2.8141	0.6832	186	4.1189	0.0040
Physics Others – Mathematics SMA	2.9878	0.6826	186	4.3773	0.0062
Physics Others – Physics SMA	3.0545	0.6979	186	4.3767	0.0255
Biology SMA – Industrial Eng. SMA	0.9721	0.2206	186	4.4068	0.0236
Biology SMA – Mathematics SMA	1.0212	0.2379	186	4.2915	0.0265

The results of the Two-Way ANOVA showed that Study Program, Type of School, and the interaction between both factors significantly influenced students' Study Duration. These findings indicate that the length of time required to complete undergraduate studies is shaped not only by disciplinary characteristics but also by students' prior educational backgrounds. The moderate effect size for Study Program suggests that differences in curriculum complexity, laboratory activities, research requirements, and academic workload across disciplines contributed meaningfully to variations in graduation time. In educational terms, this finding implies that some study programs may require stronger academic support and supervision systems to help students complete their studies within the expected timeframe.

The post hoc analysis further revealed that Biology students had significantly longer study durations compared with students from Industrial Engineering, Mathematics, Informatics, and Chemistry. This result suggests that the Biology program may involve more intensive laboratory work, field activities, and research processes that potentially extend students' time to graduation. In contrast, programs such as Informatics and Industrial Engineering may provide more structured and applied learning systems that support faster study completion. These findings highlight the importance of curriculum evaluation, academic monitoring, and mentoring programs, particularly in study programs with relatively longer completion periods.

Furthermore, the significant effect of Type of School and the interaction effect indicate that students' educational backgrounds influenced study completion differently across study programs. Students from MA backgrounds tended to require longer study durations than students from SMA backgrounds, suggesting possible differences in academic preparation and adaptation to science and technology disciplines. The interaction results also imply that compatibility between prior educational experiences and disciplinary demands plays an important role in students' academic progression. Therefore, FST may consider implementing bridging programs, academic adaptation courses, and targeted learning assistance for students from diverse educational backgrounds to improve timely graduation rates.

CONCLUSION

This study examined the effects of Study Program and Type of School on students' GPA and Study Duration using the Two-Way MANOVA approach at the Faculty of Science and Technology, UIN Sunan Kalijaga

Yogyakarta. The findings showed that Study Program significantly influenced both GPA and Study Duration, while Type of School significantly affected Study Duration but not GPA. In addition, the interaction between Study Program and Type of School significantly influenced Study Duration, indicating that the effect of educational background varied across disciplines. The post hoc analysis further revealed that Biology students tended to have longer study durations, whereas students from Informatics, Chemistry, and Industrial Engineering achieved higher GPA than Physics students.

These findings contribute to the literature by demonstrating that academic achievement in higher education is influenced more strongly by disciplinary characteristics than by school background alone. Differences in curriculum structure, academic workload, laboratory activities, and learning systems across study programs played an important role in shaping students' academic outcomes. From a practical perspective, FST should strengthen curriculum evaluation, academic mentoring, and learning support systems, particularly in study programs with relatively lower academic performance or longer study duration. Bridging and adaptation programs may also help students from diverse educational backgrounds adjust more effectively to university learning environments.

However, this study has several limitations. The sample was restricted to one faculty at a single university, limiting the generalizability of the findings. In addition, the study relied on secondary data and did not include other important variables such as motivation, socioeconomic background, or learning strategies. Some MANOVA assumptions were also violated, although robust statistics were used to minimize bias. Therefore, future research is recommended to involve broader samples, additional academic and psychological factors, and more advanced multivariate approaches to obtain a deeper understanding of students' academic achievement and study completion patterns.

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