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The Effect of Department Types on the Academic Performance of First-Year Students in the Accounting and Statistics and informatics Departments at Sulaimani University: using (MANOVA) Approach

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Abstract. *The academic performance of university students is influenced by various factors, including the department in which they are enrolled. Understanding these influences is essential for developing effective educational strategies and improving student outcomes. This study focuses on first-year students in the Accounting and Statistics and informatics departments at Sulaimani University, examining how the type of department affects their academic performance in ICT and Principles of Statistics classes. By utilizing the Multivariate Analysis of Variance (MANOVA) approach, this research aims to identify significant differences and underlying patterns in academic achievements between these two departments. The insights gained from this study can inform targeted interventions and support mechanisms to enhance educational effectiveness. Results showed that Statistics and Informatics students outperformed accounting students in both ICT and Principles of Statistics courses, with mean scores of 65.75 vs. 58.80 in ICT and 76.20 vs. 71.70 in Statistics, respectively. Box's test indicated significant differences in covariance matrices, suggesting that results should be interpreted with caution. Multivariate tests confirmed a strong departmental effect on performance, with partial eta squared values indicating substantial variance explained by the department. Levene's test showed unequal error variances for ICT but not for Statistics. Between-subjects effects analysis revealed highly significant differences between departments, with 93.6% and 97.3% of the variance in ICT and Statistics scores, respectively, explained by the department. Parameter estimates further highlighted the higher performance of Statistics and Informatics students. Overall, the findings emphasize significant academic disparities favoring the Statistics department.*

Keywords: *Accounting, Statistics& informatic, MANOVA, Multivariate Analysis, Information and communication technology (ICT).*

1. INTRODUCTION

The topic of academic achievement and the study of factors influencing it are of great importance to many specialists and researchers. Numerous studies and research have addressed this topic, and the time devoted by researchers to studying academic achievement and its influencing factors has increased significantly. Due to its importance, many studies have explored various methods to measure academic achievement and efforts to enhance it. Developing countries have invested significantly in raising academic achievement, focusing on modern educational processes and contemporary educational tools to enhance this level.

Multivariate Analysis of Variance (MANOVA) is a statistical technique used to analyze data that involves multiple dependent variables simultaneously. Unlike the traditional Analysis of Variance (ANOVA), which focuses on one dependent variable, MANOVA extends the analysis to multiple dependent variables, allowing researchers to understand the effect of independent variables on a set of dependent variables collectively. This method is particularly valuable in fields such as psychology, education, and social sciences, where multiple outcomes need to be assessed together to gain a comprehensive understanding of the phenomenon under study. The significance of MANOVA lies in its ability to detect differences between groups across multiple dependent variables, considering the correlations among these variables. This comprehensive approach provides a more nuanced understanding of the data, as it accounts for the potential interplay between dependent variables. Consequently, MANOVA has become an essential tool for researchers aiming to uncover complex relationships within their data, making it a cornerstone in multivariate statistical analysis...

2. BACKGROUND

In the 1980s and 1990s, the special applications of MANOVA began to emerge, but its use became more widespread in the early 21st century due to its direct relevance to modern technologies and developments. The increasing complexity of data in various research fields necessitated more advanced analytical techniques. MANOVA's ability to handle multiple dependent variables and consider their interactions made it particularly suited to the analysis of large and complex datasets generated by modern technologies.

Multivariate Analysis of Variance (MANOVA) is an extension of ANOVA that allows for the simultaneous analysis of multiple dependent variables. Developed to manage the complexities arising when multiple outcomes are considered, MANOVA helps determine whether changes in independent variables lead to significant variations in dependent variables. This section delves into the theoretical underpinnings of MANOVA, highlighting its importance and the contexts in which it is applied.

One powerful tool in multivariate statistics for examining group differences is multivariate analysis of variance (MANOVA). The multivariate approach to analysis of variance (MANOVA) performs comparisons of group differences in the context of two or more dependent variables (also called response or criterion variables). Unlike previous chapters where comparisons were limited to a single dependent variable at a time, contrasted with multiple groups, MANOVA allows researchers to perform a comparison of group inferences with two or more related dependent measures. This distinct advantage enables examining the possibility of an interaction between treatments and allows providing stronger support for yielding cognition for treatment differences when significance is achieved.

In MANOVA, the dependent variables are continuous and approximately normally distributed for each combination of levels of the independent variables. It is neither overly sensitive nor extremely conservative regarding violations of these assumptions. However, when data structure assumptions are violated, careful interpretation of the results is necessary.

Three major distinctions set MANOVA apart from other analyses of variance:

- MANOVA involves two or more response variables.
- Each dependent variable is tested in conjunction with other dependent variables, unlike univariate analysis of variance, which treats each dependent variable separately.
- The overall conclusions made at the end of an investigation are more comprehensive in MANOVA.

3. RESEARCH OBJECTIVE

The research objective is to investigate the impact of department type (Accounting or Statistics and informatics) on the academic performance of first-year students in ICT and Principles of Statistics classes. This study aims to identify significant performance disparities between these departments using MANOVA

3.1 Research Aims:

Investigate Departmental Impact: To examine the effect of being enrolled in either the Accounting or Statistics department on the academic performance of first-year students in ICT and Principles of Statistics classes.

Identify Performance Disparities: To identify any significant disparities in academic performance between students from the Accounting and Statistics departments using MANOVA.

Inform Educational Strategies: To provide data-driven insights that can help educators and policymakers develop targeted strategies for improving student support and teaching methods in both departments.

Test the Hypothesis: To test the hypothesis that there is no significant effect of department type on the academic performance of first-year students in the specified classes.

3.2 Research Importance

Understanding the factors that influence academic performance is essential for enhancing educational methods and outcomes. This research is important as it explores how the type of department—Accounting or Statistics—impacts the academic performance of first-year students at Sulaimani University. By identifying potential disparities and their underlying causes, this study aims to provide insights that can inform the development of targeted educational strategies and interventions, ultimately improving student success and institutional effectiveness.

3.3 Problem Statement:

Despite the extensive research on academic performance, there is limited understanding of how departmental affiliation influences student outcomes, particularly in the context of ICT and Principles of Statistics classes. At Sulaimani University, anecdotal evidence suggests that students in the Accounting and Statistics and Informatics Departments may experience different levels of academic success. However, systematic investigation into these potential disparities and their root causes is lacking. This study addresses this gap by examining whether and how the department type affects the academic performance of first-year students in these courses.

3.4 Research Hypothesis:

There is no significant effect of the department type (Accounting or Statistics and informatics) on the academic performance of first-year students in the ICT and Principles of Statistics classes at Sulaimani University.

3.5 Assumptions of MANOVA

MANOVA, like other statistical techniques, operates under a set of assumptions that must be met for the results to be valid. These assumptions include:

- Multivariate Normality: The dependent variables should follow a multivariate normal distribution within each group of independent variables.

- Homogeneity of Covariance Matrices: The covariance matrices of the dependent variables should be equal across the levels of the independent variable.
- Independence of Observations: Observations should be independent of each other.

Violations of these assumptions can lead to inaccurate results, and hence, it is crucial to test these assumptions before conducting a MANOVA.

4. STATISTICAL ANALYSIS USING MANOVA:

MANOVA is a statistical method used to analyze the variance in multiple dependent variables simultaneously. The test includes Wilks' Lambda and other statistical methods to determine the differences between groups.

MANOVA is rooted in linear algebra and involves the use of matrices to represent the data. The core idea is to decompose the total variance observed in the data into components attributable to different sources. This decomposition allows researchers to test hypotheses about the means of the dependent variables across different groups.

- **Wilks' Lambda**: One of the key statistics used in MANOVA, Wilks' Lambda tests the hypothesis that the mean vectors of the dependent variables are equal across groups. A small value of Wilks' Lambda indicates significant differences among the groups.
- **Pillai's Trace**, **Hotelling's Trace**, and **Roy's Largest Root**: These are alternative statistics that can be used to assess the multivariate effect.

4.1 Applications of MANOVA

MANOVA is widely used in various research fields where multiple outcome variables are of interest. Some common applications include:

- **Psychology**: Assessing the impact of different therapeutic interventions on a set of psychological outcomes.
- **Education**: Evaluating the effectiveness of different teaching methods on multiple academic performance indicators.
- **Medicine**: Comparing the effects of treatments on various health outcomes.

4.2 Advantages and Limitations of MANOVA

4.2.1 Advantages

- **Comprehensive Analysis**: MANOVA considers multiple dependent variables simultaneously, providing a more holistic view of the data.
- **Increased Power**: By analyzing the correlations among dependent variables, MANOVA can detect differences that might be missed by separate ANOVAs.
- **Control of Type I Error**: Conducting multiple ANOVAs increases the risk of Type I error, which is controlled by using MANOVA.

4.2.2 Limitations

- Complexity**: MANOVA is more complex to conduct and interpret than univariate techniques.**
- Assumption Sensitivity**: MANOVA's results are highly sensitive to violations of its assumptions, which require careful testing and potentially corrective measures.**
- Sample Size Requirements**: MANOVA typically requires larger sample sizes to achieve reliable results.**

5. MANOVA DESIGN MODEL:

The Multivariate Analysis of Variance (MANOVA) design model is an extension of the Analysis of Variance (ANOVA) that allows for the simultaneous analysis of multiple dependent variables. The main goal of MANOVA is to test for differences in the vector of means of the dependent variables across different groups defined by the independent variables.

Components of MANOVA Design

- Dependent Variables (DVs): Multiple outcome variables that are measured in the study.
- Independent Variables (IVs): Factors or predictors that may influence the dependent variables.
- Multivariate Test Statistics: MANOVA uses specific test statistics to determine the significance of the effects of the independent variables on the dependent variables.

6. FORMULATION OF MULTIVARIATE ONE-WAY CLASSIFICATION

When there is more than one variable measured per plot in the design of all experiments. the design is analyzed by ,multivariate analysis of variance techniques (MANOVA) techniques in short). Thus, we have the direct multivariate extension of every univariate design, but we will confine our main attention to the multivariate one-way classification which is an extension of the univariate one-way classification.

First consider a formulation resulting from agricultural experiments. Let there be k treatments which are assigned in a completely random order to some agricultural land. Suppose there are n_j plots receiving the jth treatment, $j = I, \ldots, k$. Let us assume that X_{ij} is the (p x 1) yield-vector of the ith plot receiving the jth treatment.

In general terminology, the plots are experimental designs, the treatments are conditions, and the yield is a response or outcome. We assume that theX_{ij}, are generated from the model

$$X_{ij} = \mu + \tau_j + e_{ij} \qquad i = 1,2, \ldots, n_i \quad , \quad j = 1,2, \ldots, k$$

where e_{ij} = independent$N_p(0.\Sigma)$, μ = overall effect on the yield-vector, and τ_j = effect due to the jth treatment.

This design can be viewed as a multi-sample problem, i.e. we can regard X_{ij}, $i = 1,2, \ldots, n_i$ as a random sample from $N_p(0.\Sigma)$, $j = 1,2, \ldots, k$, where

$$\mu_i = \mu + \tau_j \qquad , \quad j = 1,2, \ldots, k$$

We usually wish to test the hypothesis

$$H_0: \mu_1 = \cdots = \mu_k$$

which is equivalent to testing that there is no difference between the trea tments $\tau_1, \ldots, \tau_k$

The Likelihood Ratio Principle

The test To test H_0 against $H_1: \mu_i \neq \mu_j$ for Some $i \neq j$. Then the likelihood ratio criterion is

$A = \frac{|W|}{|T|}$ where

$$W = \sum_{j=1}^{k} \sum_{i=1}^{n} (X_{ij} - \bar{X}_j)(X_{ij} - \bar{X}_j)'$$

$T = \sum_{j=1}^{k} \sum_{i=1}^{n} (X_{ij} - \bar{X})(X_{ij} - \bar{X})'$ with

$\bar{X}_i = \frac{\sum_{i=1}^{n} X_{ij}}{n_i}$, $\bar{X} = \frac{\sum_{j=1}^{k} \sum_{i=1}^{n} X_{ij}}{n}$, $n = \sum_{i=1}^{k} n_i$

Recall that W and T are respectively the "within-samples" and ·'total'· sum of square, and products (SSP) matrices, respectively. We can further show that

$T = W + B$ (4)

where

$$B = \sum_{i=1}^{k} n_i (\bar{X}_i - \bar{X})(\bar{X}_i - \bar{X})'$$

is the "between-samples" SSP matrix. The identity (4) is the MANOVA identity.

Under Ho. it was shown that $W \sim W_p(\Sigma, n-k)$, and $B \sim W_p(\Sigma, k-1)$

Where W and B are independent. Further, if $n \geq p + k$

$$A = \frac{|W|}{|W+B|} \sim A(p, n-k, k-1)$$

Where A is a Wilks' lambda variable. We reject Ho for small values of A. Ho Can be tested by forming the MANOV A table as set out in Table below

For calculations of A, the following result is helpful : $A = \prod_{i=1}^{p} (1 + \lambda_i)^{-1}$

where $(\lambda_1, \ldots, \lambda_p)$ are the eigenvalues of $W^{-1}(B+W)$. This result follows on noting that if $(\lambda_1, \ldots, \lambda_p)$ are the eigenvalues of $W^{-1}B$. then $(\lambda_i + 1)$, $i = 1,2,\ldots,p$,are the eigenvalues of $W^{-1}(B+W)$

$$\frac{(m-p+1)\left[\,(1-\sqrt{A(p,m,2)}\,\right]}{p\sqrt{A(p,m,2)}} \sim F_{2p,2(m-p+1)}$$

Table below the common logarithms of the original measurements of (MANOVA) table

Table1. Multivariate one-way classification of

Source	d.f.	SSP matrix	Wilks' Criterion
Between samples	k-1	$B = \sum_{i=1}^{k} n_i(\bar{X}_i - \bar{X})\,(\bar{X}_i - \bar{X})'$	$A = \frac{\lvert W\rvert}{\lvert W+B\rvert} \sim A(p, n-k, k-1)$
Within samples	n-k	$W = T - B$	
Total	n-1	$T = \sum_{j=1}^{k}\sum_{i=1}^{n}(X_{ij} - \bar{X})\,(X_{ij} - \bar{X})'$	

6.1 Data Analysis

Understanding the factors that influence academic performance is crucial for enhancing educational methods and outcomes. This research aims to investigate the impact of department type—accounting and Statistics and informatics —on the academic performance of first-year students in ICT and Principles of Statistics classes. By examining these factors, we can identify potential disparities and develop strategies to improve teaching approaches and student support mechanisms. The research hypothesis posits that there is no significant effect of the department type on the academic performance of students in these classes. Through this study, we seek to contribute to the body of knowledge on educational effectiveness and provide insights for educators and policymakers.

6.2 Theoretical Framework:

The use of the MANOVA statistical method will be employed to study the effect of department types (Accounting or Statistics and informatics) on the academic performance of students in two subjects: ICT and Principles of Statistics.

6.3 Application Aspect:

The study applied MANOVA to evaluate the scientific level of first-year students in the accounting and statistics Department, using a sample of (198) students.

Table 2. Descriptive Statistics

	Department	Mean	Std. Deviation	N
ICT	Accounting	58.80	14.503	99
	Statistics and informatics	65.75	18.160	99
	Total	62.27	16.758	198
Statistic	Accounting	71.70	12.933	99
	Statistics and informatics	76.20	11.735	99
	Total	73.95	12.522	198

The descriptive statistics indicate that students in the Statistics and Informatics department performed better than those in the accounting department in both ICT and Principles of Statistics courses. Specifically, the mean score for ICT was higher for Statistics and informatics students (65.75) compared to accounting students (58.80), and similarly, the mean score for the Principles of Statistics course was higher for Statistics and informatics students (76.20) compared to accounting students (71.70).

Table 3. Box's Test of Equality of Covariance Matricesa

Box's M	13.404
F	4.418
df1	3
df2	6914880.000
Sig.	.004
Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.	
a. Design: Intercept + Department	

Table (3) shows that the Box's test indicates a significant result (p = .004), suggesting that the covariance matrices of the dependent variables are not equal across the groups. This violation of the assumption suggests that the results of MANOVA should be interpreted with caution

Table 4. Multivariate Testsa

Effect (Department)	Value	F	Hypoth esis df	Error df	Sig.	Partial Eta Squared
Pillai's Trace	0.985	95.119	4.000	392.000	0.000	0.493
Wilks' Lambda	0.025	518.145 b	4.000	390.000	0.000	0.842
Hotelling's Trace	38.465	1865.568	4.000	388.000	0.000	0.951
Roy's Largest Root	38.455	3768.569c	2.000	196.000	0.000	0.975
a. Design: Department						
b. Exact statistic						
c. The statistic is an upper bound on F that yields a lower bound on the significance level.						

The multivariate tests for the effect of the Department on the dependent variables are presented in Table (4). The Pillai's Trace test indicates a significant effect, with a value of 0.985, F(4, 392) = 95.119, p < 0.05, and a partial eta squared of 0.493. This suggests that approximately 49.3% of the variance in the dependent variables can be attributed to the Department. The Wilks' Lambda test also shows a significant effect, with a value of 0.025, F(4, 390) = 518.145, p < 0.05, and a partial eta squared of 0.842, indicating that 84.2% of the variance in the combined dependent variables is associated with the Department. Similarly, the Hotelling's Trace test results are significant, with a value of 38.465, F(4, 388) = 1865.568, p < 0.05, and a partial eta squared of 0.951, meaning that 95.1% of the variance in the dependent variables can be explained by the Department. Finally, Roy's Largest Root test confirms a significant effect, with a value of 38.455, F(2, 196) = 3768.569, p < 0.05, and a partial eta squared of 0.975. This indicates that the largest canonical correlation accounts for 97.5% of the variance in the dependent variables. Overall, these multivariate tests consistently demonstrate a highly significant effect of the Department on the dependent variables.

Table 5. Levene's Test of Equality of Error Variances[a]

		Levene Statistic	df1	df2	Sig.
ICT	Based on Mean	9.611	1	196	.002
	Based on Median	10.315	1	196	.002
	Based on Median and with adjusted df	10.315	1	195	.002
	Based on trimmed mean	10.384	1	196	.001
Statistics & informatics	Based on Mean	.044	1	196	.835
	Based on Median	.057	1	196	.812
	Based on Median and with adjusted df	.057	1	189	.812
	Based on trimmed mean	.049	1	196	.825
Tests the null hypothesis that the error variance of the dependent variable is equal across groups.					
a. Design: Intercept + Department					

For ICT, Levene's test shows significant results ($p < .05$) across all criteria, indicating that the error variances are not equal across the departments. For Principles of Statistics, Levene's test is not significant ($p > .05$), suggesting that the error variances are equal across the departments for this course.

Table 6. Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Model	ICT	770213.354[a]	2	385106.677	1426.034	0.000	.936
	Statistics & informatics	1083773.131[b]	2	541886.566	3553.727	0.000	.973
Departme	ICT	770213.354	2	385106.677	1426.034	0.000	.936
	Statistics & informatics	1083773.131	2	541886.566	3553.727	0.000	.973
Error	ICT	52930.646	196	270.054			
	Statistics & informatics	29886.869	196	152.484			
Total	ICT	823144.000	198				
	Statistics & informatics	1113660.000	198				
a. R Squared = .936 (Adjusted R Squared = .935)							
b. R Squared = .973 (Adjusted R Squared = .973)							

The tests of between-subjects effects for the dependent variables ICT (Information and Communication Technology) and Statistics & Informatics are summarized in Table (6). The results for the model indicate a significant effect on both dependent variables. For ICT, the Type III Sum of Squares is 770,213.354 with 2 degrees of freedom, leading to a mean square of 385,106.677. This results in an F value of 1426.034, which is highly significant ($p < 0.05$), and the partial eta squared is 0.936, meaning that 93.6% of the variance in ICT scores can be explained by the model. Similarly, for Statistics & Informatics, the Type III Sum of Squares is 1,083,773.131 with 2 degrees of freedom, resulting in a mean square of 541,886.566 and an F value of 3553.727, also highly significant ($p < 0.05$), with a partial eta squared of 0.973, indicating that 97.3% of the variance in Statistics & Informatics scores is accounted for by the model.

When examining the effect of the Department, the results are identical to those of the model, as the Department is the sole factor in this analysis. The error terms for ICT and Statistics & Informatics are 52,930.646 and 29,886.869 respectively, each with 196 degrees of freedom, yielding mean squares of 270.054 and 152.484 respectively. The total sums of squares for ICT and Statistics & Informatics are 823,144.000 and 1,113,660.000 respectively, each with 198 total degrees of freedom. The R Squared values are 0.936 for ICT (Adjusted R Squared = 0.935) and 0.973 for Statistics & Informatics (Adjusted R Squared = 0.973), indicating that the models fit the data very well.

Table 7. Parameter Estimates

Dependent Variable	Parameter	B	Std. Error	t	Sig.	95% Confidence Interval		Partial Eta Squared
						Lower Bound	Upper Bound	
ICT	[Department=accounting]	58.798	1.652	35.600	0.000	55.541	62.055	0.866
	[Department=Statistics]	65.747	1.652	39.808	0.000	62.490	69.005	0.890
Statistics	[Department=accounting]	71.697	1.241	57.771	0.000	69.249	74.145	0.945
	[Department=Statistics]	76.202	1.241	61.401	0.000	73.754	78.650	0.951

The parameter estimates for the dependent variables ICT and Statistics across the Accounting and Statistics departments are shown in Table (7). These estimates provide insights into the average scores for each department on the respective dependent variables, along with their significance levels, standard errors, t-values, and confidence intervals.

For the ICT dependent variable, the parameter estimate for the Accounting department is 58.798 with a standard error of 1.652. The t-value is 35.600, which is highly significant ($p < 0.05$), indicating that this parameter estimate is statistically significant. The 95% confidence interval for this estimate ranges

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from 55.541 to 62.055, and the partial eta squared is 0.866, suggesting that 86.6% of the variance in ICT scores can be attributed to the department effect.

For the Statistics department, the parameter estimate is 65.747 with a standard error of 1.652. The t-value is 39.808, which is also highly significant ($p < 0.05$). The 95% confidence interval for this estimate ranges from 62.490 to 69.005, with a partial eta squared of 0.890, indicating that 89.0% of the variance in ICT scores is due to the department effect.

For the Statistics dependent variable, the parameter estimate for the Accounting department is 71.697 with a standard error of 1.241. The t-value is 57.771, highly significant ($p < 0.05$), and the 95% confidence interval ranges from 69.249 to 74.145. The partial eta squared is 0.945, indicating that 94.5% of the variance in Statistics scores is attributable to the department effect.

Similarly, for the Statistics department, the parameter estimate is 76.202 with a standard error of 1.241. The t-value is 61.401, also highly significant ($p < 0.05$). The 95% confidence interval for this estimate ranges from 73.754 to 78.650, with a partial eta squared of 0.951, suggesting that 95.1% of the variance in Statistics scores can be explained by the department effect.

These parameter estimates reveal that both ICT and Statistics scores are significantly higher in the Statistics department compared to the Accounting department, with substantial portions of the variance in scores being explained by the department effect.

7. CONCLUSION

The study conducted a MANOVA to evaluate the academic performance of first-year students in the Accounting and Statistics departments at Sulaimani University, using a sample of 198 students. The results consistently demonstrate that students in the Statistics department outperform those in the accounting department in both ICT and Principles of Statistics courses. Descriptive statistics show higher mean scores for Statistics students in both subjects. The MANOVA results reveal a highly significant effect of the department on students' performance, with substantial portions of the variance in ICT and Statistics scores attributed to the department.

8. DISCUSSION

The findings indicate significant differences in academic performance between the two departments. Students in the Statistics department achieved notably higher scores in both ICT and Statistics courses compared to their peers in the accounting department. This discrepancy may be attributed to various factors, such as differences in curriculum rigor, teaching methods, or student preparedness. The Box's test result suggests a violation of the assumption of equality of covariance matrices, which implies that the results should be interpreted with caution. However, the robustness of the findings is supported by significant multivariate test results, including Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root, all indicating substantial departmental effects on student performance. Levene's test results show that error variances for ICT are unequal across departments, while for Statistics, they are equal. This suggests that the variability in ICT scores differs more between departments than the variability in Statistics scores. The high R-squared values for both dependent variables indicate that the models fit the data well, explaining a large proportion of the variance in student performance.

9. RECOMMENDATIONS

- Curriculum Review and Enhancement: The Accounting department may benefit from a comprehensive review of its curriculum and teaching methodologies to identify areas for improvement and to implement strategies that have proven effective in the Statistics department.
- Faculty Development: Professional development opportunities for faculty in the accounting department could focus on innovative teaching methods, use of technology in education, and strategies to enhance student engagement and performance.
- Student Support Programs: Establishing targeted support programs, such as tutoring, mentoring, and academic counseling, could help accounting students improve their performance in ICT and Statistics courses.
- Resource Allocation: Consider reallocating resources to provide additional support and materials to the accounting department, ensuring that students have access to the same quality of education and resources as those in the Statistics department.

- Further Research: Conduct qualitative studies to understand the underlying reasons for the performance disparities between departments, including student feedback, faculty perspectives, and analysis of teaching practices.
- By implementing these recommendations, Sulaimani University can work towards closing the performance gap between departments and ensuring that all students receive a high-quality education that prepares them for future academic and professional success

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