Teaching Methods – Predicting Academic Performance

The purpose of this research paper is to provide a comprehensive, step-by-step guide for conducting a **Multivariate Analysis of Variance (MANOVA)** using the Isalos Analytics Platform. MANOVA extends the traditional ANOVA by simultaneously modelling **multiple continuous dependent variables**, enabling analysts to assess how categorical factors influence a set of interrelated outcome measures. This methodology is particularly valuable in educational research, where student performance across different subjects is naturally correlated and should be analysed collectively to avoid inflating the Type I error rate and to capture the overall effect of pedagogical interventions.

MANOVA evaluates whether the mean vectors of the dependent variables differ significantly across the levels of the categorical factors. By considering the correlations among the dependent variables, MANOVA provides a more holistic understanding of group differences than running separate univariate ANOVAs for each subject.

Isalos version used: 2.1.5

The dataset used in this analysis is the **Teaching Methods Dataset**., available on Kaggle.

Source: MANOVA DATASET FOR TEACHING METHODS

This dataset contains simulated academic performance data of 100 students across five subjects: English, Math, Chemistry, Physics, and Biology. The students are divided into seven groups based on different teaching methods. The dataset is structured to facilitate the analysis of how different teaching methods affect students' scores across these subjects.

For the purposes of this MANOVA analysis, variables are classified as follows:

- **Dependent Variables (Responses) :**
  - *English*
  - *Math*
  - *Chemistry*
  - *Physics*
  - *Biology*

    — these are continuous outcome measures (test scores) to be predicted simultaneously.
- **Factors (Categorical Predictors) :**
  - *Teaching Method* (comprising 7 distinct instructional groups)

    — this categorical variable represents the pedagogical approach whose multivariate effect on student performance is of primary interest.

- **Covariates (Continuous Predictors) :** — *None.*
  This is a pure MANOVA design, meaning there are no continuous covariates to control for. The analysis focuses solely on the effect of the categorical teaching method on the multivariate response profile.

Step 1: Import Data from file

Firstly, launch the Isalos Analytics Platform (version 2.1.2). Then, in the left spreadsheet panel, create a new tab by clicking **File** and choose **Open** to load the teaching methods dataset (or simply copy-paste the data from your spreadsheet).

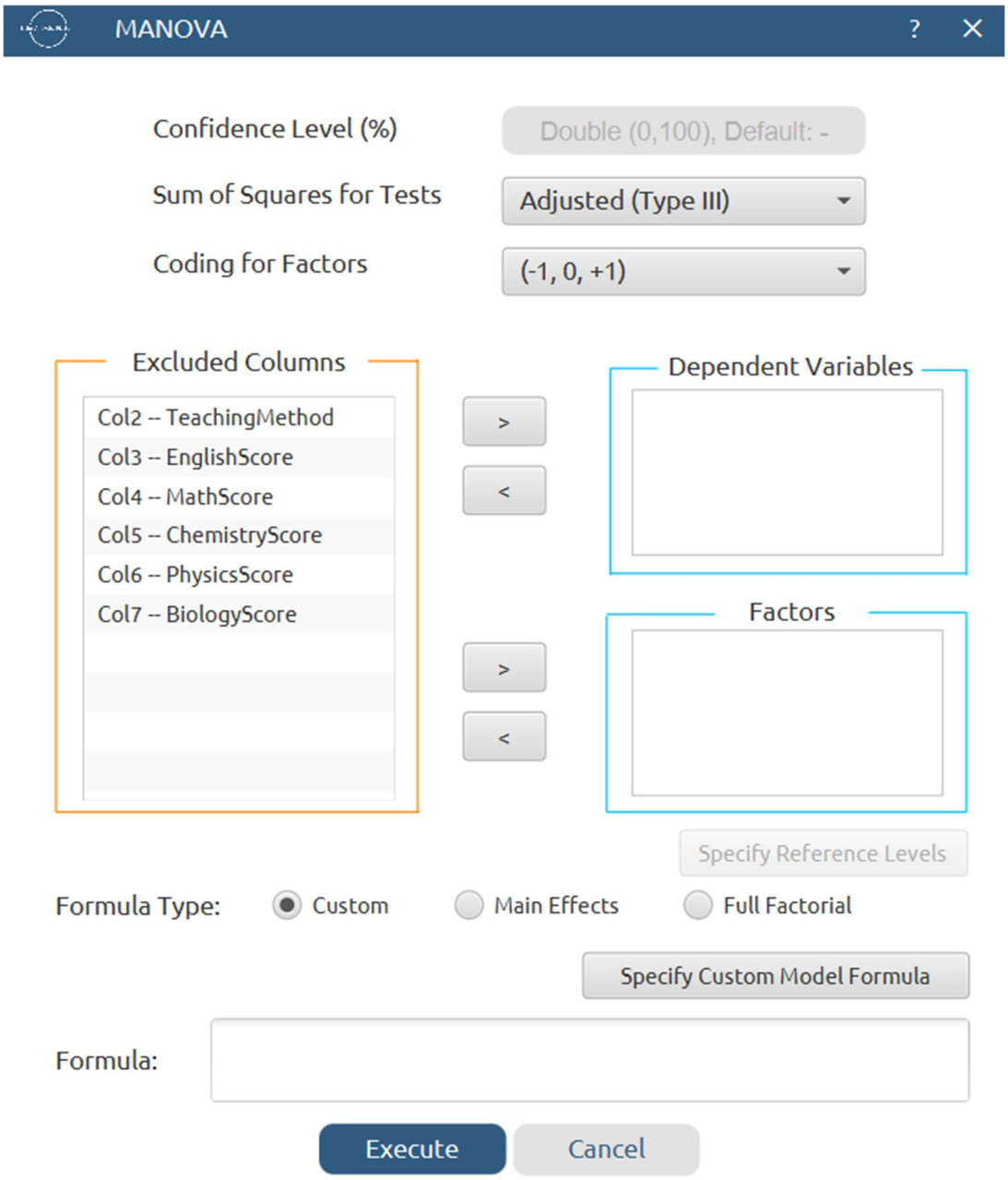
Col1	Col2 (S)	Col3 (I)	Col4 (I)	Col5 (I)	Col6 (I)	Col7 (I)
User Row ID	TeachingMethod	EnglishScore	MathScore	ChemistryScore	PhysicsScore	BiologyScore
1	Differentiated Instruction	85	88	90	87	89
2	Differentiated Instruction	87	90	92	89	91
3	Differentiated Instruction	89	85	88	86	88
4	Differentiated Instruction	84	87	85	88	87
5	Differentiated Instruction	88	89	90	90	89
6	Differentiated Instruction	90	92	91	91	92
7	Differentiated Instruction	85	86	87	85	86
8	Differentiated Instruction	87	88	89	87	88
9	Differentiated Instruction	88	85	86	88	87
10	Differentiated Instruction	86	87	88	86	89
11	Differentiated Instruction	89	88	90	89	90
12	Differentiated Instruction	87	89	91	87	88

Step 2: Access the MANOVA function

Navigate to the MANOVA analysis module through the main menu by choosing the following path:

Statistics → Analysis of (Co)Variance → MANOVA

Then, you will see the MANOVA configuration window:



Step 3: Configure MANOVA parameters

The MANOVA model can be specified with varying levels of complexity. The model is expressed as:

$$[\text{English, Math, Chemistry, Physics, Biology}] = \beta_0 + \beta_1(\text{Teaching Method}) + \varepsilon$$

This is a multivariate linear model where the five dependent variables are regressed onto the single categorical factor (Teaching Method). Since there are no covariates, this is a straightforward MANOVA design.

Important:

The inclusion of interaction terms is not applicable here, as we have only one categorical factor. However, MANOVA assumes homogeneity of variance-covariance matrices across groups (Box's M test). If this assumption is violated, robust test statistics (e.g., Pillai's Trace) should be prioritized. For this basic demonstration, we focus on the **main-effects model**.

Steps in Isalos Analytics Platform:

In the MANOVA configuration window, set the following parameters:

* Confidence Level (%) : 95
* **Dependent Variables:** Select
    - Col3 – English Score,
    - Col4 — Math Score,
    - Col5 – Chemistry Score,
    - Col6 – Physics Score,
    - Col7 – Biology Score

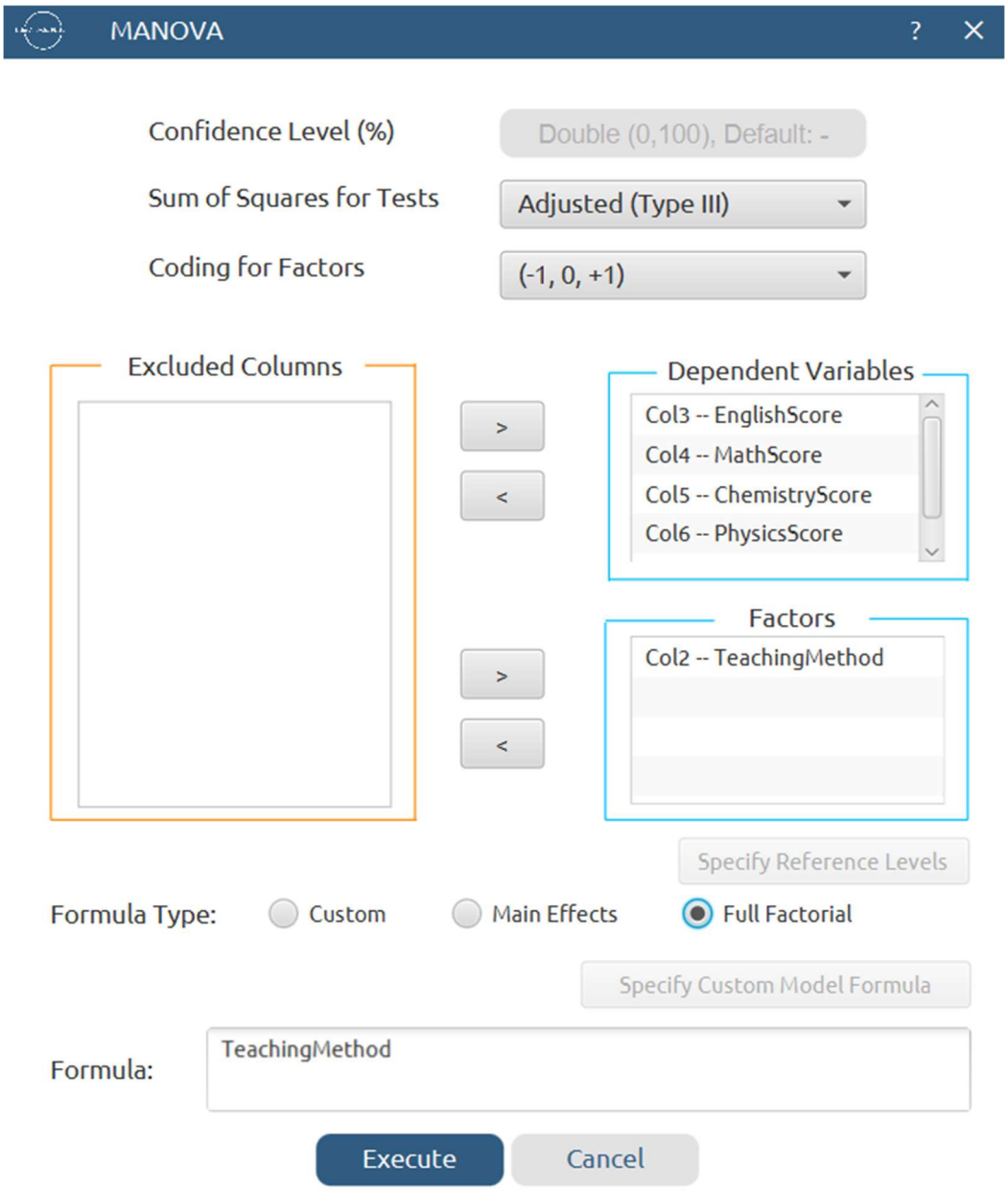
and move them to the ***Dependent Variables*** field.

* **Factors (Categorical Predictors):** Move
    - Col2 – Teaching Method

to the ***Factors*** field.

* **Covariates (Continuous Predictors):** — *Leave this field empty*, as there are no continuous covariates in this design.

Then, for **Formula Type**, choose **Full Factorial**. The formula preview will display the multivariate model as shown below:



After configuring all parameters:

* Review all selections to ensure accuracy.
* Click the **Execute** button to run the MANOVA analysis.
* Wait for the computation to complete (processing time depends on dataset size and the number of dependent variables).

Step 4: Results

The analysis results will be displayed in the right spreadsheet panel. The output typically includes the following components:

Source	Dependent Variable	DF	Adj SS	Adj MS	F-Value	P-Value	Significant
TeachingMethod	EnglishScore	6	1681.6916417	280.2819403	115.1801049	0.0	Yes
	MathScore	6	1820.2026307	303.3671051	110.2948824	0.0	Yes
	ChemistryScore	6	1856.1868065	309.3644678	111.0960371	0.0	Yes
	PhysicsScore	6	2263.0755977	377.1792663	153.3353591	0.0	Yes
	BiologyScore	6	1932.7063670	322.1177278	153.9936731	0.0	Yes
Corrected Model	EnglishScore	6	1681.6916417	280.2819403	115.1801049	0.0	Yes
	MathScore	6	1820.2026307	303.3671051	110.2948824	0.0	Yes
	ChemistryScore	6	1856.1868065	309.3644678	111.0960371	0.0	Yes
	PhysicsScore	6	2263.0755977	377.1792663	153.3353591	0.0	Yes
	BiologyScore	6	1932.7063670	322.1177278	153.9936731	0.0	Yes
Error	EnglishScore	93	226.3083583	2.4334232			
	MathScore	93	255.7973693	2.7505093			
	ChemistryScore	93	258.9731935	2.7846580			
	PhysicsScore	93	228.7644023	2.4598323			
	BiologyScore	93	194.5336330	2.0917595			
Corrected Total	EnglishScore	99	1908.0000000				
	MathScore	99	2076.0000000				
	ChemistryScore	99	2115.1600000				
	PhysicsScore	99	2491.8400000				
	BiologyScore	99	2127.24				

Step 5 : Residual Analysis & Assumption's checks

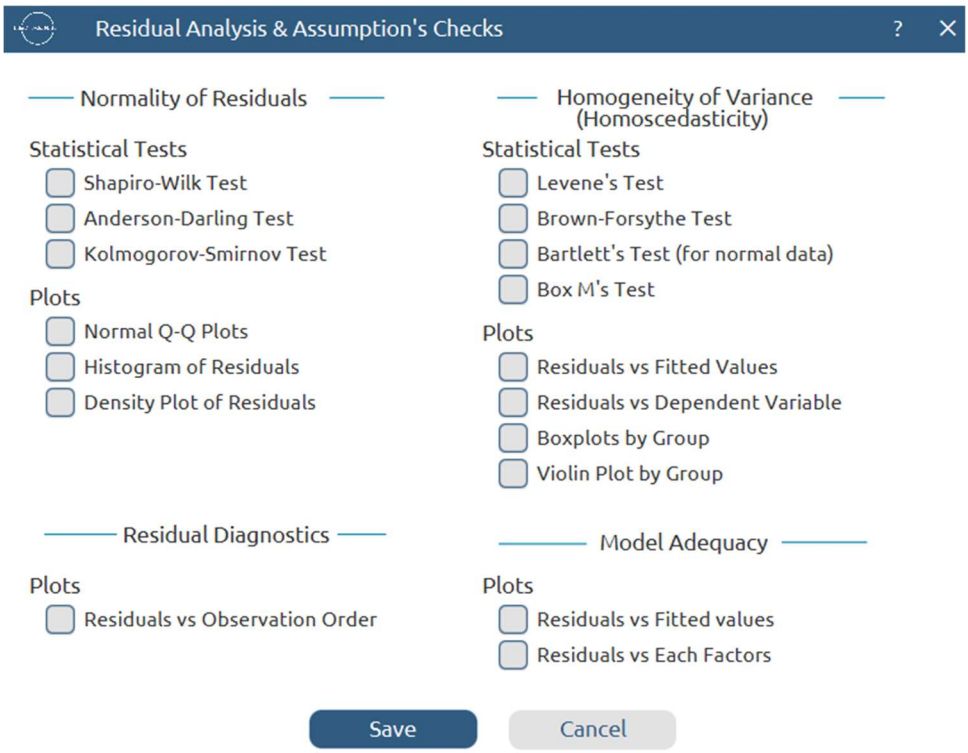
Choose

Statistics → Analysis of (Co)Variance → MANOVA

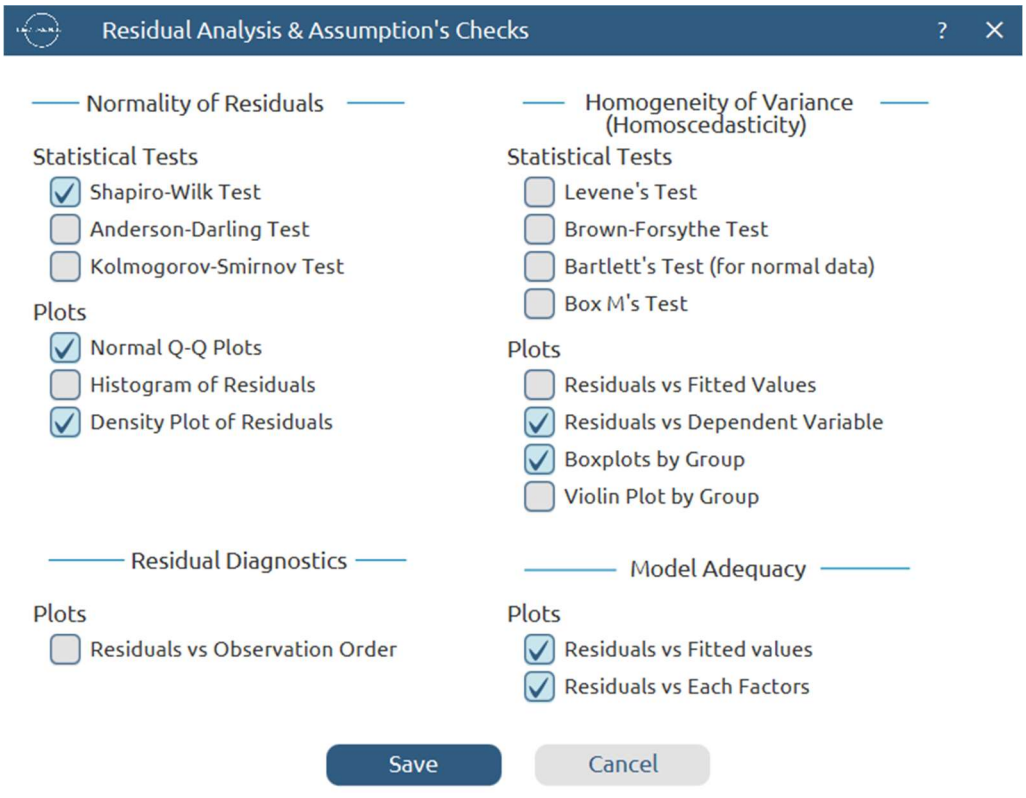
and choose

Residual Analysis & Assumption's Checks.

You get the following window:



then choose the tests you want. For example, choose the following:



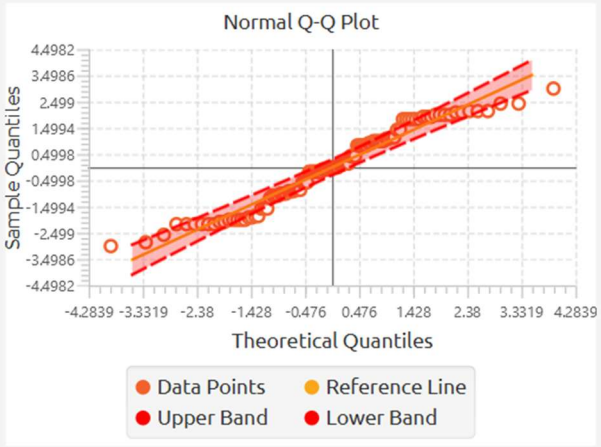
After that, click execute and you get the results (some of them below):

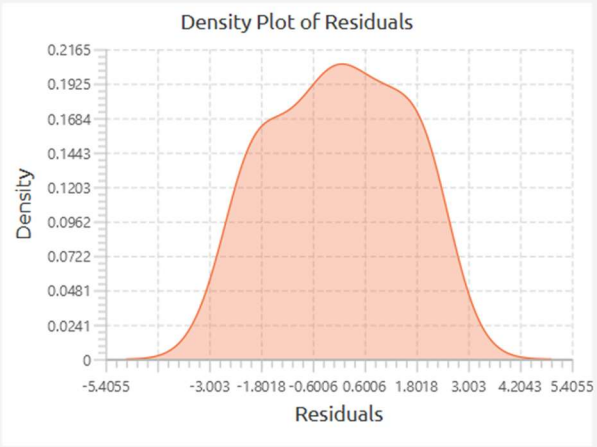
MANOVA - EnglishScore

Normality of Residuals

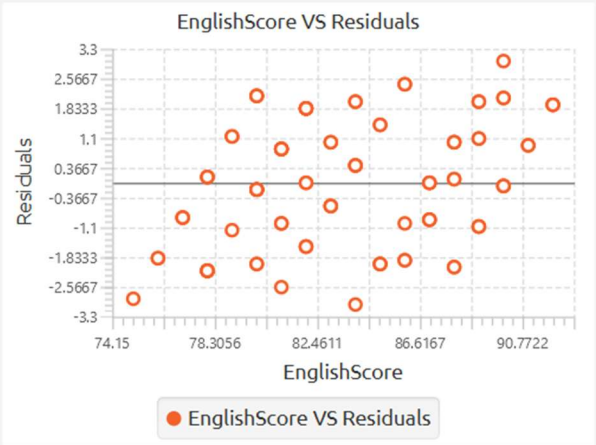
Statistical Tests

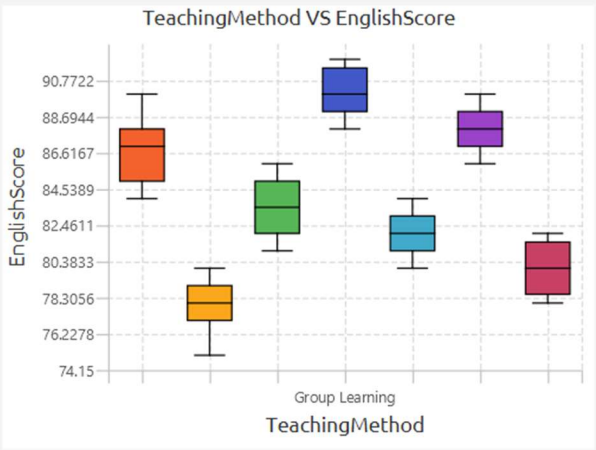
Normality Test	Statistic	Prob	P-value	Decision
Shapiro Wilk	0.955	0.998	0.002	Reject Null Hypothesis



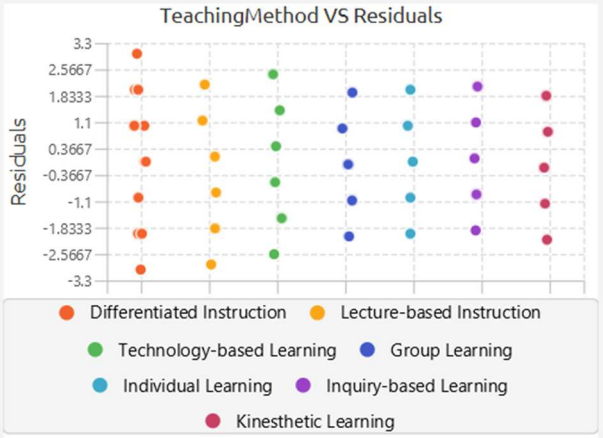


Homogeneity of Variance





Model Adequacy

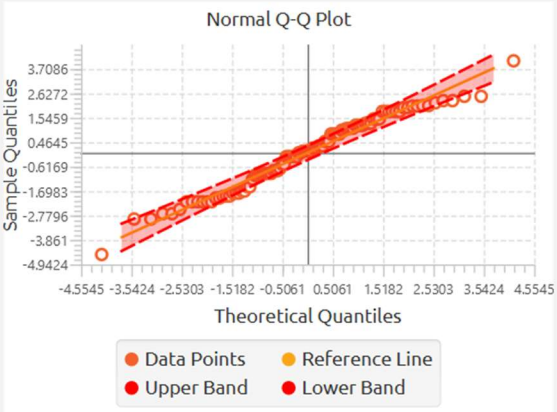


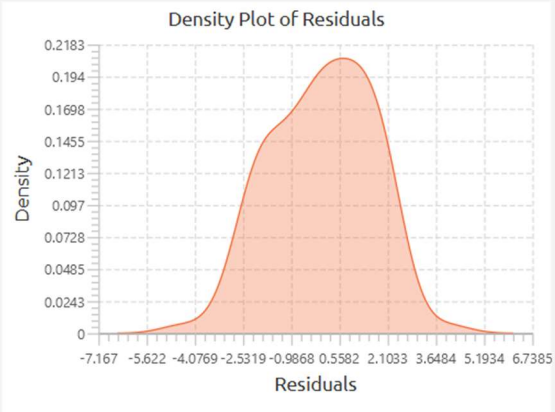
MANOVA - MathScore

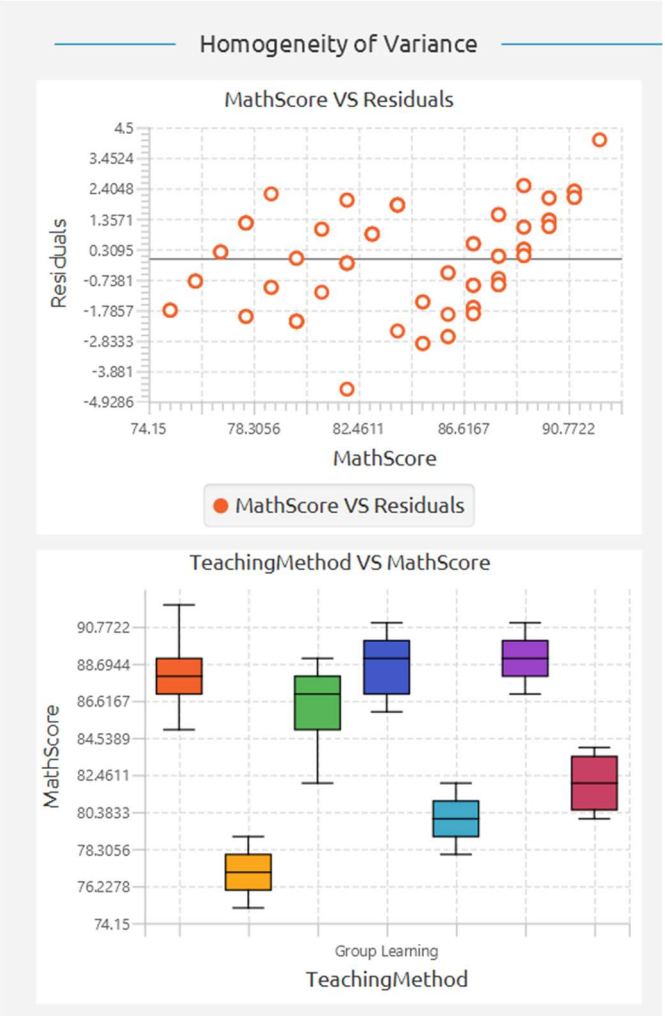
Normality of Residuals

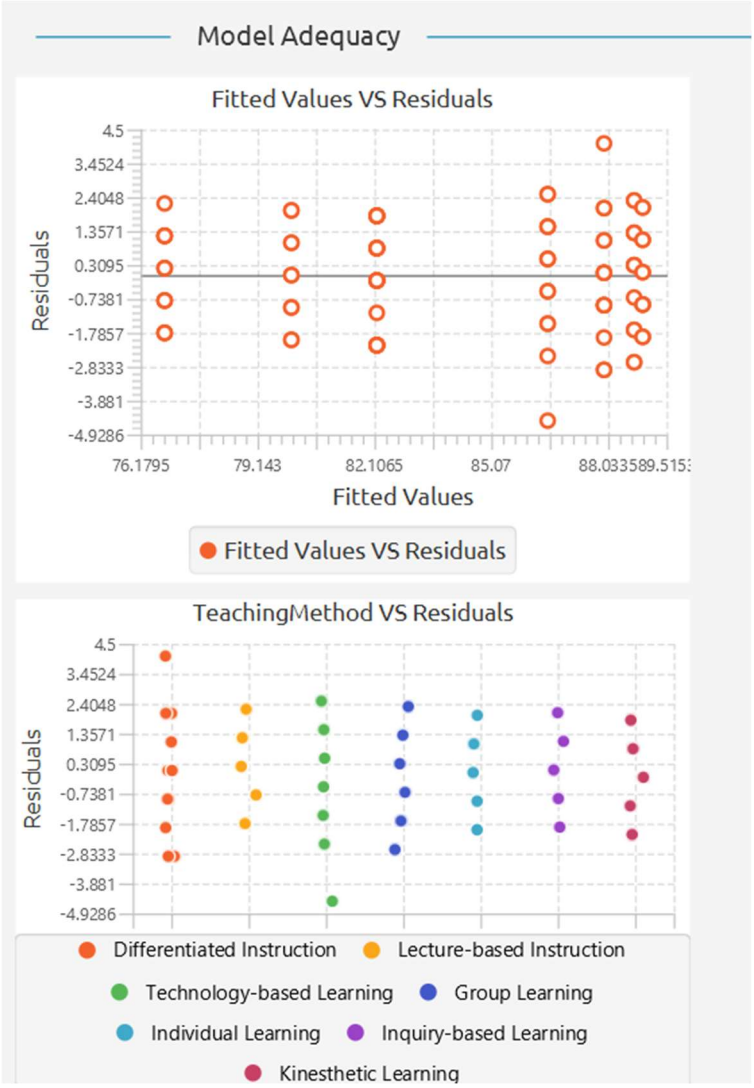
Statistical Tests

Normality Test	Statistic	Prob	P-value	Decision
Shapiro Wilk	0.977	0.919	0.081	Fail to Reject Null Hypothesis






Homogeneity of Variance
MathScore VS Residuals
Residuals
4.5
3.4524
2.4048
1.3571
0.3095
-0.7381
-1.7857
-2.8333
-3.881
-4.9286
74.15
78.3056
82.4611
86.6167
90.7722
MathScore
MathScore VS Residuals
TeachingMethod VS MathScore
MathScore
90.7722
88.6944
86.6167
84.5389
82.4611
80.3833
78.3056
76.2278
74.15
Group Learning
TeachingMethod


Model Adequacy
Fitted Values VS Residuals
Residuals
4.5
3.4524
2.4048
1.3571
0.3095
-0.7381
-1.7857
-2.8333
-3.881
-4.9286
76.1795
79.143
82.1065
85.07
88.033589.515
Fitted Values
Fitted Values VS Residuals
TeachingMethod VS Residuals
Residuals
Differentiated Instruction
Lecture-based Instruction
Technology-based Learning
Group Learning
Individual Learning
Inquiry-based Learning
Kinesthetic Learning