How to Perform a Repeated Measures ANOVA in SPSS: A Step-by-Step Guide

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March 15, 2026

Understanding the Fundamentals of Repeated Measures ANOVA

The **Repeated Measures ANOVA** is a sophisticated statistical procedure used to determine if there are statistically significant differences between the means of three or more groups where the same subjects are measured under multiple conditions. Unlike a standard **One-Way ANOVA**, which assumes independent groups, the repeated measures design accounts for the correlation between observations taken from the same individual. This approach is highly valued in clinical research and psychology because it reduces the **error variance** by controlling for individual differences, thereby increasing the **statistical power** of the analysis.

When conducting research using **SPSS**, it is essential to recognize that this test is technically a **within-subjects design**. This means that every participant is exposed to every level of the independent variable, which in many cases is time or different experimental treatments. By using the same subjects across all conditions, researchers can effectively observe how a specific intervention changes a outcome over time, making it an ideal choice for longitudinal studies or trials testing various dosages of a medication on the same patient group.

The core objective of utilizing a **Repeated Measures ANOVA** is to test the **null hypothesis**, which posits that the means of all treatment levels are equal. If the analysis yields a **statistically significant** result, it suggests that at least one of the conditions differs from the others. However, the test itself does not specify which pairs are different, necessitating the use of post-hoc tests to pinpoint the exact nature of the variations within the data set.

The Experimental Scenario: Evaluating Drug Efficacy

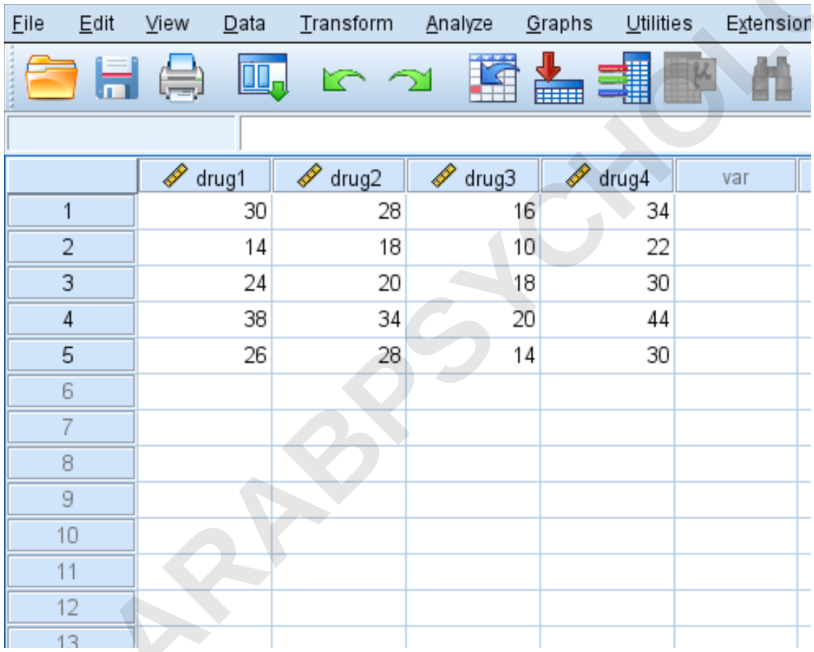
To illustrate the application of a **Repeated Measures ANOVA** in **SPSS**, consider a clinical study where researchers are investigating the impact of four distinct pharmacological agents on patient reaction times. In this hypothetical experiment, five patients are selected, and each patient is administered four different drugs sequentially. The reaction time for each patient is recorded after each administration, resulting in four unique measurements per subject. This design is classic for repeated measures because the "subject" (the patient) serves as their own control across the "levels" (the drugs).

The primary research question in this scenario is whether the mean reaction time differs significantly across the four drugs. Because we are measuring the same five individuals four separate times, the observations are not independent. If we were to use a standard ANOVA, we would violate the assumption of independence, leading to inaccurate results. The **Repeated Measures ANOVA** is specifically designed to handle this dependency by partitioning the variance into within-subject and between-subject components, allowing for a more precise estimation of the treatment effect.

Before proceeding with the analysis in **SPSS**, it is critical to ensure that the data is organized correctly. Each row in the **data set** should represent a single subject, while each column represents a different level of the within-subjects factor. In this case, we would have one column for each of the four drugs. This wide-format structure is a requirement for the **General Linear Model** procedures within the software, ensuring that the system recognizes the link between the repeated observations of each patient.

Step 1: Data Entry and Variable Organization in SPSS

The initial phase of the analysis involves entering the raw data into the **SPSS** Data Editor. You must create four separate variables, which we will name Drug_1, Drug_2, Drug_3, and Drug_4. Each of these columns will contain the reaction times (measured in seconds) for the five patients. It is vital to maintain the order of the patients across the rows so that the first row consistently represents the data for Patient 1, the second row for Patient 2, and so forth. This ensures that the software correctly calculates the within-subject variances.



	drug1	drug2	drug3	drug4	var
1	30	28	16	34	
2	14	18	10	22	
3	24	20	18	30	
4	38	34	20	44	
5	26	28	14	30	
6					
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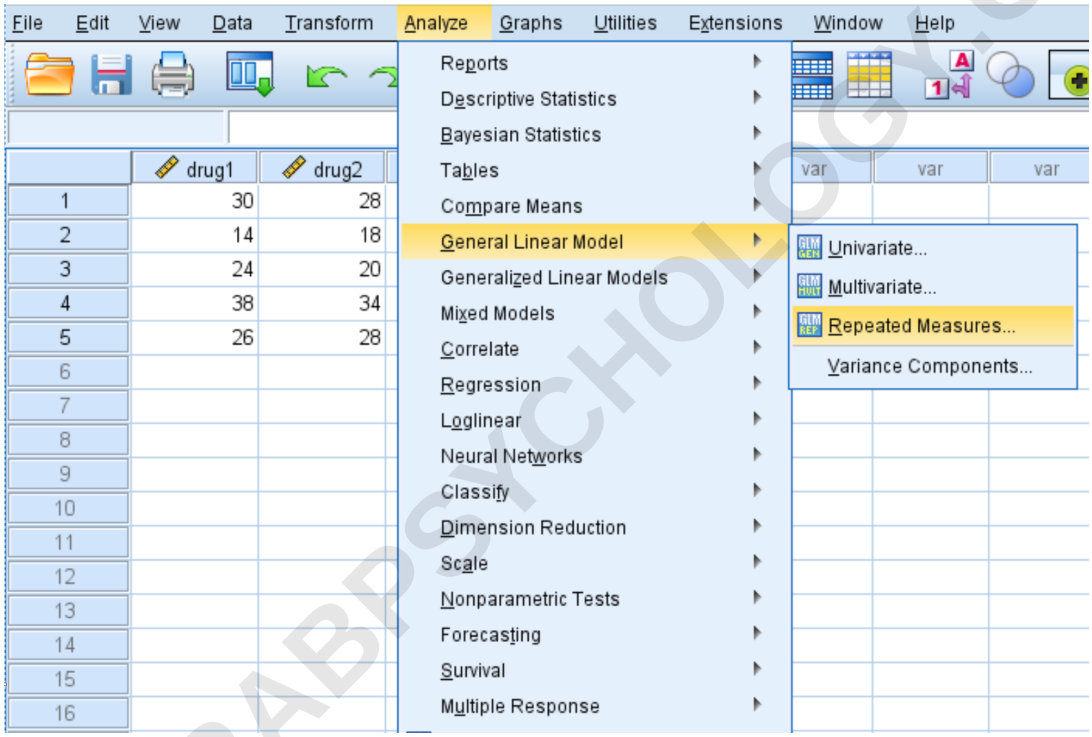
Once the data is entered, it is a good practice to check for **outliers** or missing values that could skew the results. In a small sample size like this (N=5), even a single extreme value can have a profound impact on the **F-statistic** and the resulting **p-value**. Proper labeling in the "Variable View" tab is also recommended, as clear labels for the drug types will make the final output tables much easier to interpret and report in a formal academic or professional setting.

After verifying the data integrity, the user is ready to move into the analytical menu. The setup in **SPSS** for repeated measures is slightly more complex than a standard t-test or ANOVA because it

requires the user to define the factor structure before selecting the variables. This structural definition is what allows the **General Linear Model** to treat the multiple columns as different levels of the same underlying experimental condition.

Step 2: Accessing the Repeated Measures Dialog

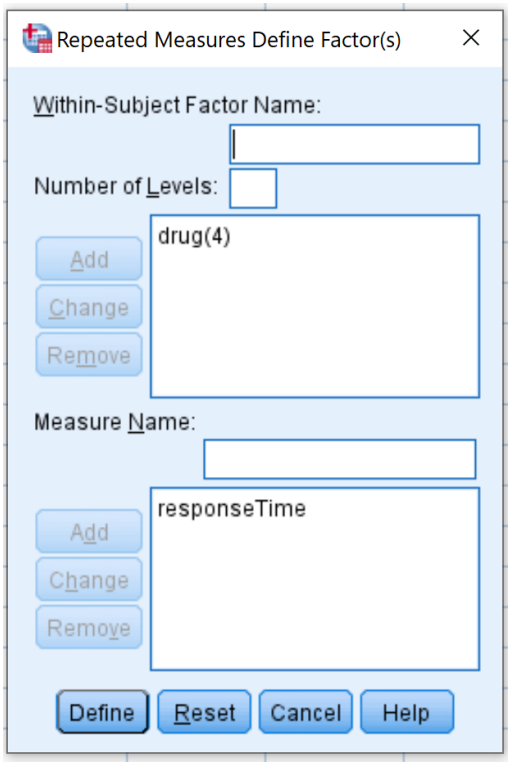
To begin the formal analysis, navigate to the top menu bar in **SPSS** and select **Analyze**. From the dropdown menu, hover over **General Linear Model** and then click on **Repeated Measures**. This action will open the "Repeated Measures Define Factor(s)" dialog box. This specific interface is used to tell the software how many levels your within-subject factor has and what you are actually measuring, which is a prerequisite for the subsequent variable assignment.



Within this dialog, you must first define the **Within-Subject Factor Name**. In our drug study, a descriptive name like "DrugType" or simply "drug" is appropriate. Next, you must specify the **Number of Levels**. Since we are testing four different drugs, enter "4" into this field and click the **Add** button. This informs the software that it should expect four distinct measurements for each subject. You can also optionally define a **Measure Name**, such as "ReactionTime," to provide further clarity to the generated output tables.

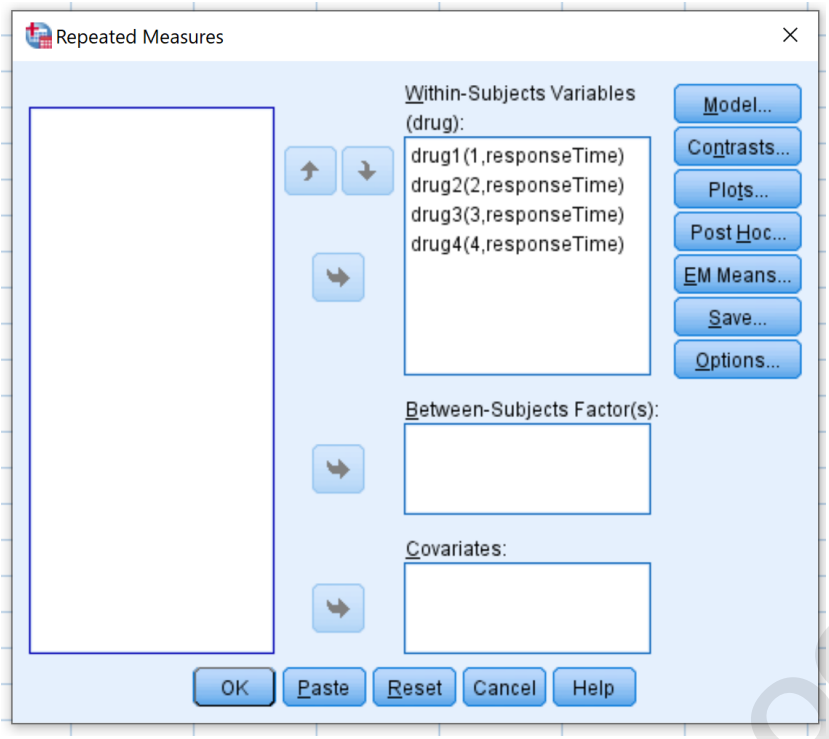
Once the factors and levels are defined, clicking the **Define** button will transition you to the main "Repeated Measures" dialog box. This is where the actual mapping of your data columns to the experimental levels takes place. It is at this stage that the distinction between the variable names

in your data sheet and the conceptual factors of your experimental design is finalized. Proper execution of this step is critical for the software to correctly calculate the **degrees of freedom** for the within-subject effects.



Step 3: Defining Within-Subject Variables and Factor Levels

In the main "Repeated Measures" window, you will see a list of your variables on the left and a box titled **Within-Subjects Variables** on the right. You must move the four drug variables (Drug_1 through Drug_4) into this box. The order in which you move them should correspond to the levels you defined in the previous step. For example, the first variable moved will represent level 1 of the "drug" factor, the second will be level 2, and so on. This mapping ensures that the **Repeated Measures ANOVA** correctly identifies which data column belongs to which experimental condition.

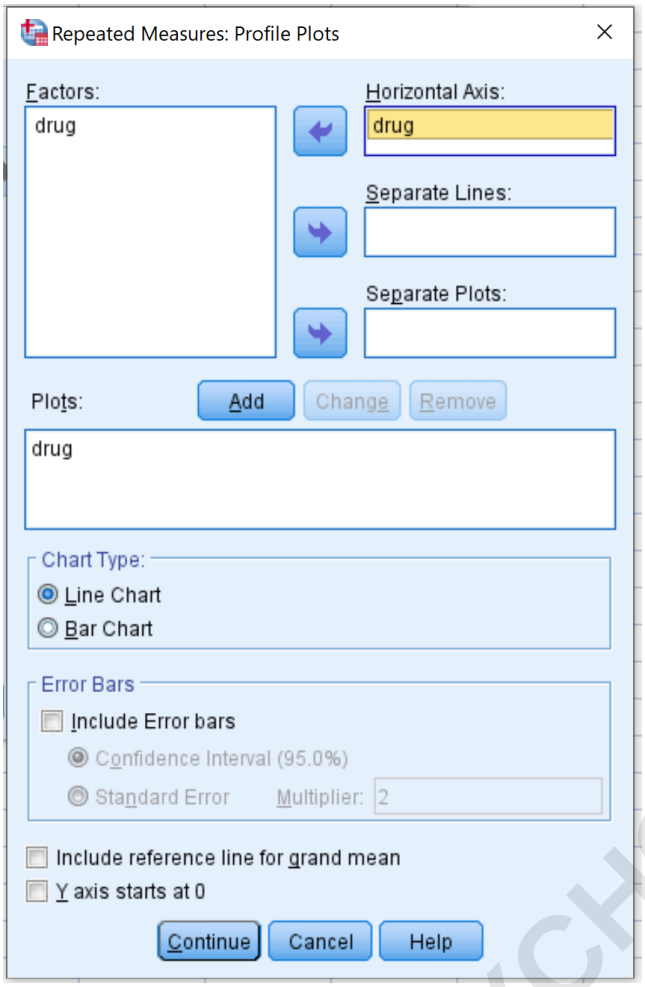


While in this dialog, it is often useful to configure additional settings to enhance the depth of the analysis. For instance, researchers should check the "Options" button to select "Descriptive statistics" and "Estimates of effect size," such as **partial eta-squared**. These metrics provide essential context to the **p-value**, helping to determine not just if the results are significant, but how large the effect of the drug treatment actually is in a practical sense.

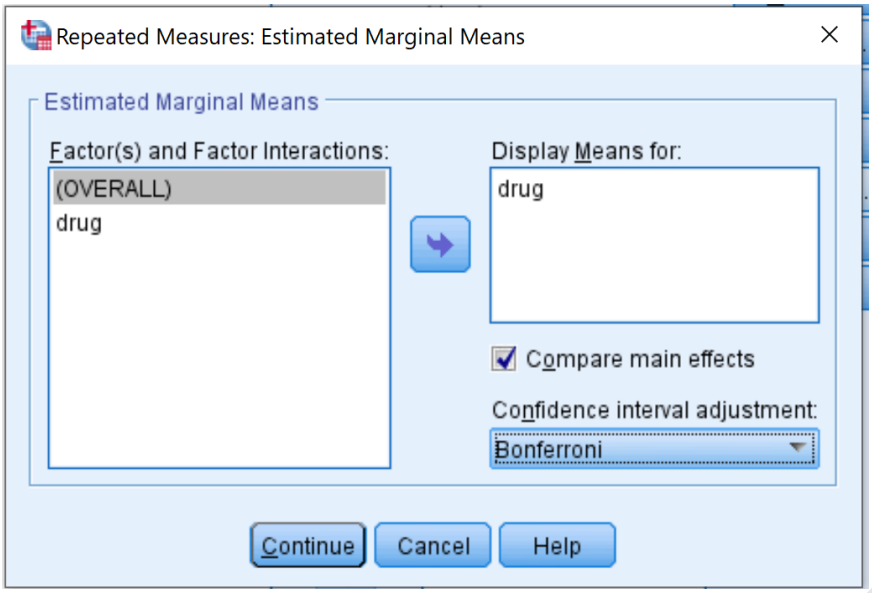
Furthermore, this is the stage where you can handle the **assumption of sphericity**. Sphericity is the requirement that the variances of the differences between all possible pairs of within-subject conditions are equal. If this assumption is violated, the **F-statistic** becomes positively biased, leading to an increased **Type I error** rate. **SPSS** automatically provides Mauchly's Test of Sphericity, but it is prudent to be prepared to use the **Greenhouse-Geisser correction** if the assumption is not met.

Step 4: Configuring Graphical Plots for Visualization

Visualization is a powerful tool for interpreting complex statistical interactions. To generate a plot of the results, click the **Plots** button in the "Repeated Measures" dialog. Drag the "drug" factor into the **Horizontal Axis** box and then click **Add**. This will instruct **SPSS** to create a line graph showing the mean reaction time for each of the four drug conditions. Such visual aids are indispensable for identifying trends, such as whether reaction times generally increase or decrease across the different treatments.



After adding the plot configuration, click **Continue** to return to the main dialog. Graphical representations often reveal nuances in the data that are not immediately apparent from numerical tables alone. For instance, a plot might show that while the overall ANOVA is significant, the difference is primarily driven by one specific drug that has a vastly different reaction time compared to the other three. This visual insight can guide the interpretation of the **post-hoc analysis** and help in forming a more cohesive narrative of the experimental findings.



Once all configurations--including factor definitions, variable assignments, and plots--are set, click **OK** to execute the procedure. **SPSS** will then process the data and generate a comprehensive output viewer containing several tables and charts. Understanding how to navigate this output is the most critical part of the process, as it contains the evidence required to support or reject your **null hypothesis** regarding the drugs' effects.

Step 5: Interpreting the Within-Subjects Effects Table

The most important table in the output is titled **Tests of Within-Subjects Effects**. This table provides the primary **F-statistic** and the associated **p-value** for the drug factor. When reviewing this table, you will see multiple rows, including "Sphericity Assumed," "Greenhouse-Geisser," "Huynh-Feldt," and "Lower-bound." It is a common scientific standard to use the **Greenhouse-Geisser correction** values, as they are more conservative and adjust the **degrees of freedom** to account for potential violations of the sphericity assumption.

In our drug example, the Greenhouse-Geisser row indicates an **F-statistic** of 24.759 with a **p-value** of .001. Because this p-value is well below the traditional **significance level** of .05, we can confidently reject the **null hypothesis**. This result provides strong evidence that the mean reaction times are not all the same across the four drugs; at least one drug significantly alters the reaction time compared to the others.

Tests of Within-Subjects Effects

Measure: responseTime

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
drug	Sphericity Assumed	698.200	3	232.733	24.759	.000
	Greenhouse-Geisser	698.200	1.815	384.763	24.759	.001
	Huynh-Feldt	698.200	3.000	232.733	24.759	.000
	Lower-bound	698.200	1.000	698.200	24.759	.008
Error(drug)	Sphericity Assumed	112.800	12	9.400		
	Greenhouse-Geisser	112.800	7.258	15.540		
	Huynh-Feldt	112.800	12.000	9.400		
	Lower-bound	112.800	4.000	28.200		

While the main effect tells us that a difference exists, it does not specify which drugs are different from one another. To determine the specific relationships between individual drugs, we must look at the **Pairwise Comparisons**. This is a vital distinction in **ANOVA**; the "omnibus" test (the main F-test) only indicates that some difference exists somewhere in the data, acting as a gateway to more detailed **post-hoc analysis**.

Step 6: Analyzing Pairwise Comparisons and Post-Hoc Tests

Since the initial test was **statistically significant**, we proceed to the **Pairwise Comparisons** table. This table compares every possible pair of drugs to see where the specific differences lie. To control for the increased risk of **Type I error** that occurs when performing multiple tests, **SPSS** often applies a **Bonferroni correction**. This adjustment ensures that our conclusions remain robust and that we do not mistakenly identify a difference as significant purely by chance.

Pairwise Comparisons

Measure: responseTime

(I) drug	(J) drug	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	.800	1.625	1.000	-7.082	8.682
	3	10.800	2.577	.083	-1.700	23.300
	4	-5.600*	.748	.010	-9.230	-1.970
2	1	-.800	1.625	1.000	-8.682	7.082
	3	10.000	2.280	.071	-1.062	21.062
	4	-6.400	1.600	.097	-14.162	1.362
3	1	-10.800	2.577	.083	-23.300	1.700
	2	-10.000	2.280	.071	-21.062	1.062
	4	-16.400*	2.227	.011	-27.204	-5.596
4	1	5.600*	.748	.010	1.970	9.230
	2	6.400	1.600	.097	-1.362	14.162
	3	16.400*	2.227	.011	5.596	27.204

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Reviewing the p-values in the comparison table reveals the following results for our study:

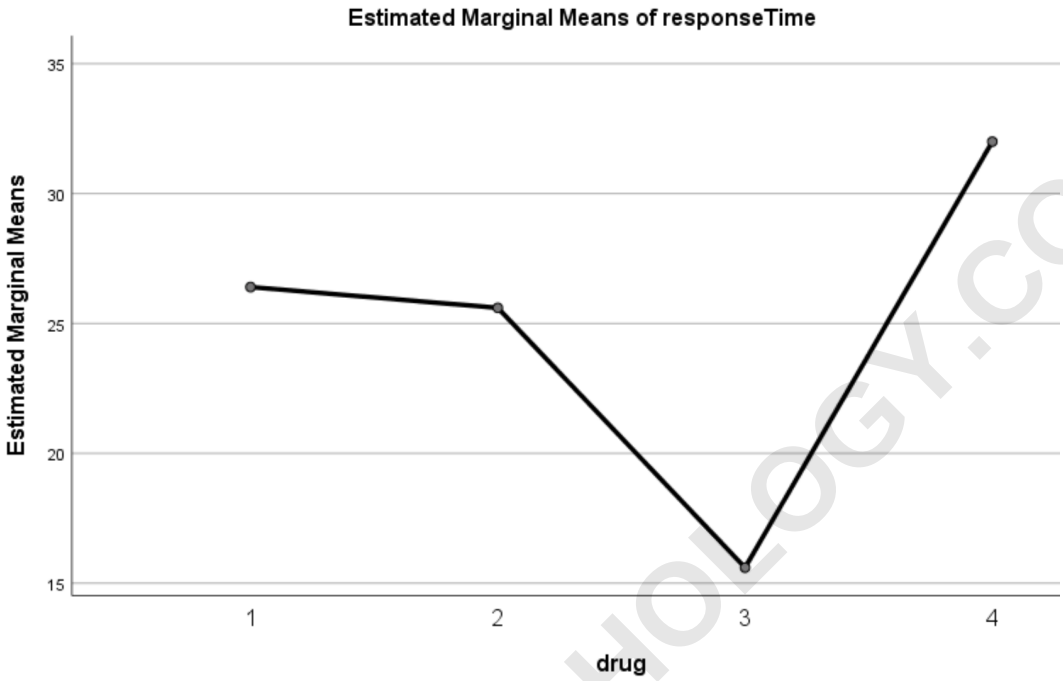
Drug 1 vs. Drug 2: p = 1.000 (No significant difference)
Drug 1 vs. Drug 3: p = .083 (No significant difference)
Drug 1 vs. Drug 4: p = .010 (Statistically significant)
Drug 2 vs. Drug 3: p = .071 (No significant difference)
Drug 2 vs. Drug 4: p = .097 (No significant difference)
Drug 3 vs. Drug 4: p = .011 (Statistically significant)

These results indicate that Drug 4 is the primary outlier in terms of performance, showing a significant difference in reaction times when compared to both Drug 1 and Drug 3. However, other comparisons did not reach the .05 threshold. This level of detail is essential for clinical applications, as it allows researchers to identify which specific treatments are actually producing a unique effect on the subjects.

Step 7: Final Visualization and Professional Reporting

The final component of the **SPSS** output is the **Plot of Estimated Marginal Means**. This graph provides a clear visual summary of the reaction time averages across the four conditions. By

looking at the slope and the points on the line, you can easily see the "dip" or "spike" associated with specific drugs. In our example, the plot confirms that response times varied noticeably, with certain drugs causing much faster or slower reaction times than others, mirroring the findings from our pairwise comparison table.



When reporting these results in a research paper or clinical report, it is standard to include the **F-statistic**, the **degrees of freedom**, and the **p-value**. A formal summary might look like this: "A one-way **Repeated Measures ANOVA** was conducted to determine the effect of four different drugs on patient reaction times. The results indicated a **statistically significant** effect of drug type on response time (F(1.51, 6.03) = 24.76, p = 0.001)."

Additionally, the report should mention the results of the **post-hoc analysis**. For example: "Follow-up **Bonferroni** pairwise comparisons revealed that reaction times were significantly different between Drug 1 and Drug 4 (p = .010) and between Drug 3 and Drug 4 (p = .011). No other significant differences were observed. These findings suggest that Drug 4 has a distinct impact on patient reaction times compared to the other tested pharmacological agents." This structured approach ensures that all aspects of the **data analysis** are communicated clearly and professionally.