

# Perform a Kruskal-Wallis Test in R

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## RECOMMENDED CITATION

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The [Kruskal-Wallis Test](#) is a powerful **non-parametric** statistical procedure used to determine whether there are statistically significant differences among the medians of three or more independent groups. Unlike tests that rely on assumptions about population distribution, the Kruskal-Wallis test examines differences based on the ranks of the data, offering resilience against non-normal distributions.

It is frequently cited as the non-parametric equivalent of the one-way [Analysis of Variance \(ANOVA\)](#). While ANOVA tests for differences in means and requires strict adherence to normality and homogeneity of variances, the Kruskal-Wallis Test bypasses these stringent requirements by focusing instead on the central tendency, specifically the [median](#). This makes it an invaluable tool when working with ordinal data or data that severely violates the assumptions necessary for parametric testing.

This comprehensive tutorial will guide you through the process of performing and interpreting the Kruskal-Wallis Test using the statistical programming environment, [R](#). We will explore a practical example, step-by-step, ensuring a clear understanding of both the code implementation and the resulting statistical inferences.

## Choosing the Kruskal-Wallis H Test

Before implementing any statistical test, researchers must rigorously evaluate whether their data meets the required assumptions. Parametric tests, such as ANOVA, assume that observations within each group are independent, that the dependent variable is measured on a continuous scale, and critically, that the residuals are normally distributed and variances are equal across groups (homoscedasticity). When these assumptions are violated--particularly the assumption of normality--the results derived from ANOVA may become unreliable or misleading.

The Kruskal-Wallis H Test offers a robust alternative under these circumstances. It relies on a less restrictive set of assumptions. Specifically, it assumes that the variable is measured on at least an ordinal scale and that observations are independent. Crucially, it tests the null hypothesis that the population medians are equal, rather than the means. By ranking the data across all groups and then analyzing the sums of ranks for each group, the test effectively minimizes the impact of outliers and non-normal distributions, thereby ensuring a more reliable result when dealing with skewed or unusual data distributions.

Therefore, if preliminary data analysis (e.g., using graphical methods or formal tests like Shapiro-Wilk) indicates severe skewness, heavy tails, or significant outliers, the Kruskal-Wallis test becomes the appropriate analytical choice for comparing three or more groups. This decision ensures statistical rigor when analyzing complex real-world data sets that rarely conform perfectly to idealized normal distributions.

## Example Scenario: Evaluating Fertilizer Effectiveness

To illustrate the application of the Kruskal-Wallis test, consider a typical agricultural research scenario. Suppose a team of researchers aims to determine if three distinct types of fertilizer (labeled A, B, and C) result in statistically different levels of plant growth. To ensure experimental control, they randomly select 30 identical plant specimens. These 30 plants are then randomly allocated into three equal groups, resulting in 10 plants per fertilizer group.

Each group receives its assigned fertilizer treatment for a standardized period of one month. At the conclusion of this period, the researchers meticulously measure the height (growth) of every single plant. The central objective of the analysis is to use the Kruskal-Wallis test to formally assess the [median](#) growth across these three groups. The goal is to determine if the variation in plant height observed is simply due to random chance, or if there is a statistically significant effect attributable to the type of fertilizer used.

The following steps outline the procedure for setting up this data and executing the test within the R environment, allowing us to arrive at a data-driven conclusion regarding the effectiveness of the fertilizers.

### Step 1: Entering and Structuring Data in R

The first crucial step in any statistical analysis using R is preparing the data in a format that the software can readily process. For group comparison tests like Kruskal-Wallis, the data should ideally be structured in a long format, containing one column that specifies the group (the independent variable) and another column listing the outcome measurement (the dependent variable).

We begin by creating a data frame in R that consolidates the growth measurements of all 30 plants along with their corresponding fertilizer group assignment. We use the built-in R functions `rep()` and `data.frame()` to efficiently structure this dataset. The `group` variable is defined as a categorical factor, while `height` serves as the continuous measurement variable.

Reviewing the structure of the data frame confirms that the data is correctly assigned, with the first six rows demonstrating the pairing of fertilizer type (A, B, or C) and the measured height. This data preparation ensures that the subsequent statistical function can correctly parse the relationship between the categorical predictor and the continuous outcome.

```
#create data frame
```

```
df <- data.frame(group=rep(c('A', 'B', 'C'), each=10),
```

```
height=c(7, 14, 14, 13, 12, 9, 6, 14, 12, 8,
```

```
15, 17, 13, 15, 15, 13, 9, 12, 10, 8,
```

```
6, 8, 8, 9, 5, 14, 13, 8, 10, 9))
```

```
#view first six rows of data frame
```

```
head(df)
```

```
group height
```

```
1 A 7
```

```
2 A 14
```

```
3 A 14
```

```
4 A 13
```

```
5 A 12
```

```
6 A 9
```

## Step 2: Executing the Kruskal-Wallis Test in R

With the data frame correctly loaded and structured, the next step involves running the actual statistical test. R provides a straightforward, base function for this procedure: `kruskal.test()`. This function utilizes the standard R formula syntax, where the dependent variable is specified on the left side of the tilde (~) and the independent grouping variable is specified on the right.

The syntax `height ~ group` instructs R to compare the distribution of the `height` variable across the categories defined by the `group` variable within the specified data frame (`data = df`). The `kruskal.test()` function automatically handles the internal process of ranking the data across all 30 observations and calculating the H statistic based on the summed ranks for each fertilizer group. This simplifies the execution significantly, allowing the researcher to focus on interpretation rather than manual calculation.

Executing the following command yields the primary output, which includes the test statistic (Kruskal-Wallis chi-squared), the degrees of freedom (df), and the essential **p-value**. These elements are necessary for determining whether to reject the null hypothesis.

```
#perform Kruskal-Wallis Test
```

```
kruskal.test(height ~ group, data = df)
```

```
Kruskal-Wallis rank sum test
```

```
data: height by group
```

```
Kruskal-Wallis chi-squared = 6.2878, df = 2, p-value = 0.04311
```

### Step 3: Interpreting the Statistical Results

The interpretation of the Kruskal-Wallis Test output revolves around the fundamental principles of hypothesis testing. We must first clearly state the **null hypothesis (H<sub>0</sub>)** and the alternative hypothesis (H<sub>A</sub>) specific to this test. The null hypothesis posits that there is no difference in the central tendency across the populations from which the samples were drawn, while the alternative hypothesis suggests that at least one group median differs from the others.

The hypotheses are formally defined as follows:

**The null hypothesis (H<sub>0</sub>):** The population medians for all groups (Fertilizer A, B, and C) are equal. Mathematically,  $\text{MedianA} = \text{MedianB} = \text{MedianC}$ .

**The alternative hypothesis (H<sub>A</sub>):** At least one population median is different from the others.

From the R output, we obtained a test statistic, the Kruskal-Wallis chi-squared value, of **6.2878**, with 2 degrees of freedom. Crucially, the corresponding **p-value** is **0.04311**. To draw a conclusion, we compare this p-value to a predetermined significance level (alpha,  $\alpha$ ), which is conventionally set at 0.05.

Since the calculated p-value (0.04311) is less than the typical significance level ( $\alpha = 0.05$ ), we reject the null hypothesis (H<sub>0</sub>). Rejecting H<sub>0</sub> means we have sufficient statistical evidence to conclude that the median plant growth is not the same across all three fertilizer groups. In practical terms, this suggests that the type of fertilizer used leads to statistically significant differences in plant growth height. Had the p-value been greater than 0.05, we would have failed to reject the null hypothesis, concluding that there was insufficient evidence to claim a difference among the fertilizer types.

### Further Analysis: Post-Hoc Testing and Limitations

While the Kruskal-Wallis test successfully indicates that a significant difference exists among the groups, it does not specify *which* pairs of groups differ. For instance, in our example, we know that A, B, and C are not all equal, but we do not know if A differs from B, A differs from C, or B differs from C. To determine these specific pairwise comparisons, a follow-up analysis, known as a **post-hoc test**, is required.

Appropriate post-hoc procedures for the Kruskal-Wallis test include Dunn's Test or the Conover-Iman Test. These tests perform multiple pairwise comparisons while applying a correction (such as the Bonferroni or Holm adjustment) to control the family-wise error rate, preventing an inflation of Type I errors that would occur if simple Mann-Whitney U tests were performed without correction. Implementing these post-hoc analyses in R typically requires external packages, such as `dunn.test` or `rstatix`, which provide specialized functions for ranking and comparison

adjustments.

In summary, the Kruskal-Wallis test provides the essential first step by confirming overall differences among groups when parametric assumptions are violated. Researchers must remember that while non-parametric tests are robust to distribution issues, they generally possess less statistical power than their parametric counterparts (like ANOVA) when the parametric assumptions *are* met. Therefore, choosing the correct test based on data characteristics remains paramount for rigorous statistical analysis.

## **Additional Resources**

The following tutorials explain how to perform other common statistical tests in R, offering further opportunities to expand your data analysis toolkit: