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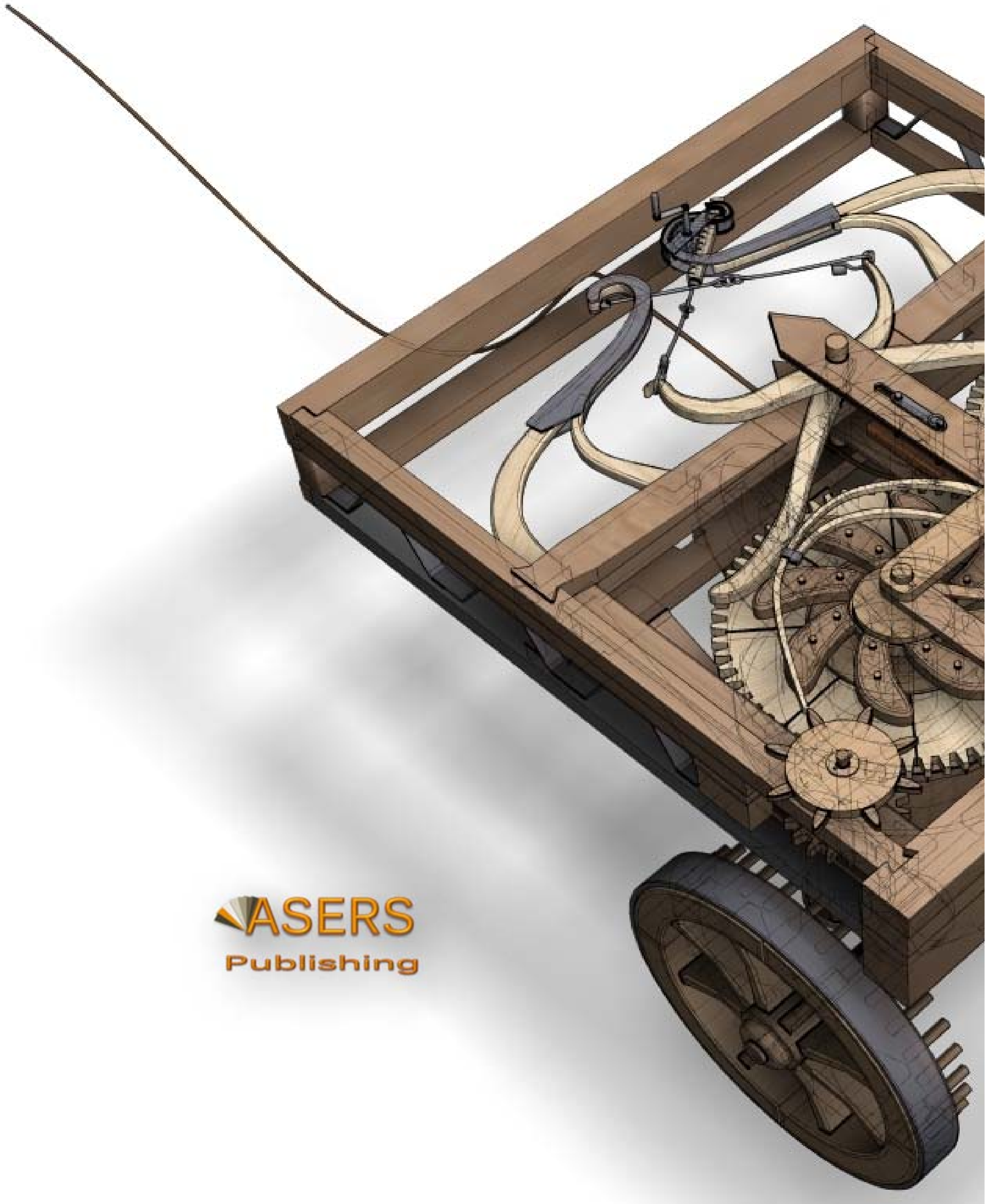

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Volume XIII, Issue 15, 2022
Journal of Research in Educational Sciences

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Reporting and Interpreting One-Way Analysis of Variance (ANOVA) Using a Data-Driven Example: A Practical Guide for Social Science Researchers

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Abstract

One-way (between-groups) analysis of variance (ANOVA) is a statistical tool or procedure used to analyse variation in a response variable (continuous random variable) measured under conditions defined by discrete factors (classification variables, often with nominal levels). The tool is used to detect a difference in means of 3 or more independent groups. It compares the means of the samples or groups in order to make inferences about the population means. It can be construed as an extension of the independent t-test. Given the omnibus nature of ANOVA, it appears that most researchers in social sciences and its related fields have difficulties in reporting and interpreting ANOVA results in their studies. This paper provides detailed processes and steps on how researchers can practically analyse and interpret ANOVA in their research works. The paper expounded that in applying ANOVA in analysis, a researcher must first formulate the null and in other cases alternative hypothesis. After the data have been gathered and cleaned, the researcher must test statistical assumptions to see if the data meet those assumptions. After this, the researcher must then do the necessary statistical computations and calculate the F-ratio (ANOVA result) using a software. To this end, the researcher then compares the critical value of the F-ratio with the table value or simply look at the p-*value against the established alpha. If the calculated critical value is greater than the table value, the null hypothesis will be rejected and the alternative hypothesis is upheld.*

Keywords: analysis; ANOVA; statistical method; assumptions; educational research.

JEL Classification: D83; C10; I21.

Introduction

The acronym "ANOVA" is a statistical technique that simply stands for analysis of variance. In the quest to extent *t* and the *z* test, Ronald Fisher in 1918 came out the model ANOVA. This implies that prior to the use of ANOVA, the *t* -test and *z*-test were commonly used and apply in research works (Stoline 1981; Algina & Olejnik 2003). The rational for the development of ANOVA is based on the assumption that *t* and the *z* test, could be applied for more than two groups of variables. This test is also called the Fisher analysis of variance, which is used to do the analysis of variance between and within the groups whenever the groups are more than two (Algina & Olejnik 2003; Green & Salkind 2003).

ANOVA determines whether the groups created by the levels of the independent variable are statistically different by calculating whether the means of the treatment levels are different from the overall mean of the dependent variable (Montgomery 2017; Burke 2017). If any of the group means is significantly different from the overall mean, then the null hypothesis is rejected (Ostertagová & Ostertag 2013; Naik & Reddy 2018). ANOVA uses the F-test for statistical significance. This allows for comparison of multiple means at once, because the error is calculated for the whole set of comparisons rather than for each individual two-way comparison (which would happen with a t-test) (Ostertagová & Ostertag 2013; Beins 2021). The F-test compares the variance in each group mean from the overall group variance. If the variance within groups is smaller than the variance between groups, the F-test will find a higher F-value, and therefore a higher likelihood that the difference observed is real and not due to chance (Ostertagová & Ostertag 2013; Beins 2021).

By its application in educational research, the one-way analysis of variance (ANOVA) is used to determine whether there are any statistically significant differences between the means of two or more independent (unrelated) groups (Quirk 2012). One-way ANOVA is an **omnibus statistical test meaning that its** test whether the explained variance in a set of data is significantly greater than the unexplained variance (Warner 2013, Beins 2021; González-Rodríguez *et al.* 2012; Mrkvicka *et al.* 2016). Similar to *t*-tests (independent or dependent sample t-tests), one-way ANOVA can be extremely useful for instance, in finding out whether testing performance among students varies due to the groups they belong to or based on their grade point average, etc (Warner 2013, Beins 2021; González-Rodríguez, *et al.* 2012). To explore the parameters for of one-way ANOVA testing, a dataset must be provided and its variables reviewed to determine whether they are suitable for use with this approach (Tamhane 2017; Sadooghi-Alvandi *et al.* 2012; McHugh 2011).

Clearly, scholars have pointed out that the need for ANOVA arises from the error of alpha level inflation, which increases Type 1 error probability (false positive) and is caused by multiple comparisons (Armstrong *et al.* 2002; Kim 2017). ANOVA uses the statistic F, which is the ratio of between and within group variances. The main interest of analysis is focused on the differences of group means; however, ANOVA focuses on the difference of variances. Illustrated figures in any ANOVA analysis serves as a suitable guide to understand how ANOVA determines the mean difference problems by using between and within group variance differences (Yang 2019; Kim 2017; Vijayvargiya 2009).

The rigorous and robust nature of ANOVA could pose some challenges for researcher practitioners who could want to use one-way analysis of variance (ANOVA) in their studies. The present paper used conceptual illustration with data driven example to explain how one-way analysis of variance (ANOVA) can be used. The paper further expounded how the difference in mean scores can be explained by comparing the variances rather by the means themselves. The paper finally detailed how Post-Hoc Tests are used and interpreted.

1. Testing Assumptions of ANOVA

In the work of Warner (2013), it is averred that in order to ascertain whether or not the proposed variables are appropriate for one-way ANOVA testing, six assumptions must be met. First, the dependent variable to be evaluated must be continuous either an interval or ratio scale. Second, the independent variable must be categorical since this is a comparison of differentiated group means. In addition, it is important that the cases included within the population have values for both the dependent and independent variables if a case has no values for either variable, it is to be excluded (Warner 2013; González-Rodríguez *et al.* 2012).

Also, the groups to be tested should be independent. Simply put, there should be no relationship between the subjects in each sample nor should a subject in either group have the ability to influence results in the opposing group (Naik & Reddy 2018; Yang 2019). If this assumption is not met, an inaccurate *p*-value is the likely result. Third, there must be no relationship between the participants and observations in each group. Fourth, there must be no outliers as they contribute to non-normal population distributions. Fifth, the samples to be tested must be random and (approximately) normally distributed. Last but not least, variances must share uniformity (homogeneity). When this assumption is violated and the sample sizes for each group differ, a Welch ANOVA would need to be run along with a post-hoc test (George & Mallery 2016; Beins 2021).

In addition to the above assumptions postulated by George and Mallery (2016), Cortina and Nouri (2017) also asserted that, in using ANOVA, the population in which samples are drawn should be normally distributed. Another significant assumption is independence of cases. This means that the sample cases should be independent of each other. In furtherance to the above, homogeneity is one of the testable assumptions. In ANOVA analysis, homogeneity means that the variance between the groups should be approximately equal. The assumption of homogeneity of variance can be tested using tests such as Levene's test or the Brown-Forsythe Test (Weissgerber *et al.* 2018; Naik & Reddy 2018).

In testing for these assumptions, normality of the distribution of the population can be tested using plots, the values of skeweness and kurtosis, or using tests such as Shpiro-Wilk or Kolmogorov-Smirnov. The assumption of independence can be determined from the design of the study. It is important to note that ANOVA is not robust to violations to the assumption of independence. This is to assert that, even if a researcher violates the assumptions of homogeneity or normality, you can conduct statistical procedures that will still enable the researcher to conduct the ANOVA but he or she is likely to arrive at wrong conclusions and implications (Cortina & Nouri 2017; Naik & Reddy 2018).

Table 1. Assumptions testing Summary Table

Assumptions	How to check	What to do if the assumption is not met
Residuals should be normally distributed	Use the Save menu within GLM to request the standardised residuals for each subject to be added to the dataset and then use ***Analyze »» Descriptive Statistics »»Explore*** to produce histograms/ Q-Q plot / Shapiro Wilk tests of residuals	if the residuals are very skewed, the results of the ANOVA are less reliable. The KruskallWallis test should be used instead of ANOVA. For more details on checking normality, see the Checking normality in SPSS resource. For help carrying out a Kruskall-Wallis test, refer to the Kruskall-Wallis in SPSS resource
Homogeneity (equality) of variance: The variances (SD squared) should be similar for all the groups.	The Levene's test is carried out if the Homogeneity of variance test option is selected in the Options menu. If $p > 0.05$, equal variances can be assumed.	If $p < 0.05$, the results of the ANOVA are less reliable. The Welch test is more appropriate and can be accessed via the Options menu using Analyze»» Compare Means »» One-way ANOVA. The Games Howell post hoc test should also be used instead of Tukey's

Source: Modified from Statstutor Community Project, 2020

2. Estimating Effect Size (ES) in ANOVA

In using ANOVA in educational research, it is always imperative to estimate the effect size. In calculating the effect size, the values can be considered small, medium or large. In checking this values, Cohen's tables for effect size is often used to determine what the value for a small, medium or large effect size would be for an ANOVA (Lee 2016; Ludbrook 2000; González-Rodríguez *et al.* 2012). If from running an ANOVA the researcher determines that he or she do not have statistically significantly different groups, but have a large effect size, the researcher might want to rerun the ANOVA test with a larger sample size (Mrkvicka *et al.* 2016). A large effect size without statistical significance could be an indication that significance can be reached with a larger sample (Cardinal & Aitken 2006; Tabachnick & Fidell, 2007).

3. Practical Application of ANOVA in Testing Hypothesis in a Study (Data-Driven Example)

$H_0$1: Number of years of widows in their widowhood will not have statistically significant difference in their quality of life (QoL).

H_A1: Number of years of widows in their widowhood will have statistically significant difference in their quality of life (QoL).

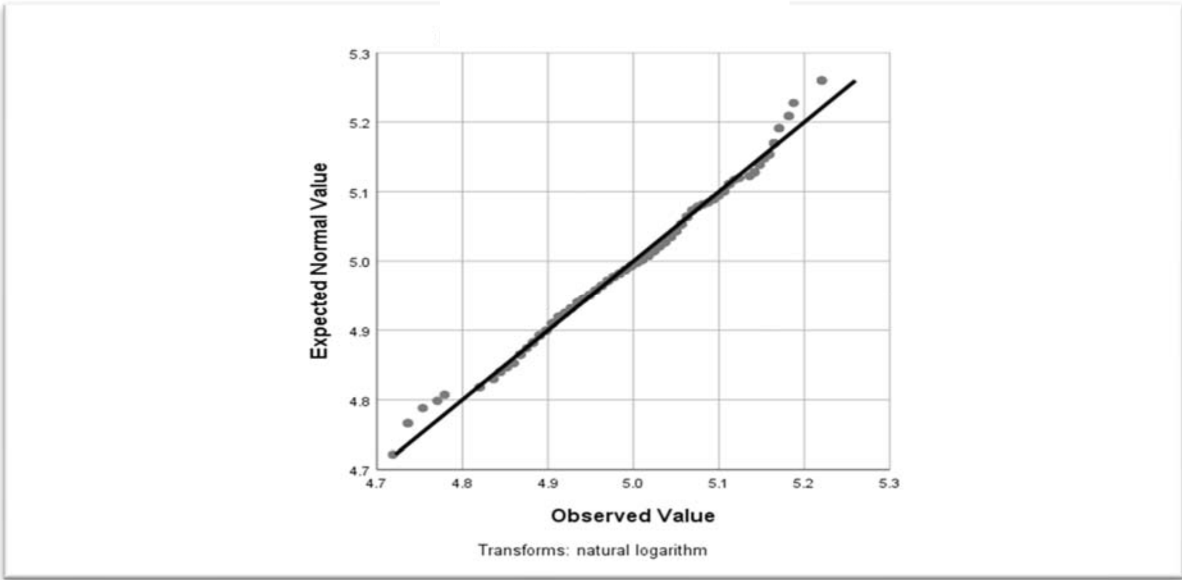
At an alpha level of .05 confidence, the hypothesis was tested to find out whether the difference will exist in the number of years in widowhood and quality of life among young widows. To assess difference in the number of years in widowhood and quality of life among young widows, between-groups one-way analysis of variance (ANOVA) was deemed appropriate for the study. To obtain the scores for the analysis, the responses on the quality of life among young widows were transformed into a single variable using the SPSS Software, (v.25). This was classified or coded as the dependent variable (QoL). The data on questionnaire was made up of an independent variable that is the ages of the widows which is categorical (nominal) and the dependent variable was QoL which was measured on continuous scale. The between-groups one-way analysis of variance (ANOVA) was conducted to determine whether there are any statistically significant differences among the means of the independent groups (number of years in widowhood-NYiW) and the QoL of the widows.

4. Normality Assumption of Data

In testing normality for ANOVA test, the Shapiro-Wilk procedure may be used to test normality in samples with fewer than 2000 observations (Burke 2017; González-Rodríguez *et al.* 2012). The raw data deviate severely from normality (at $p<0.001$) with right skewness and/or high kurtosis, and this justifies application of the normalizing logarithmic transformation. The ANOVA model is just an approximation for the data, and ANOVA assumptions may not be satisfied completely. With normal data but heterogeneous variances, ANOVA is robust for balanced or nearly balanced designs but not for highly unbalanced designs. In the setting of normal data, heterogeneous variances, and an unbalanced design, one might use Welch's ANOVA to accommodate unequal variances.

In furtherance to the above, with homogeneous variances but non-normal data, ANOVA is robust for balanced designs with large samples but not for unbalanced design or small samples ($n<5$ per group). In the setting of non-normal data, homogeneous variances, and a small sample or highly unbalanced design, a nonparametric procedure such as the Kruskal-Wallis test may be preferred over One-way ANOVA. If the data are not normally distributed and variances are heterogeneous, a transformation may be necessary. It is instructive to note that, at the research design stage, an investigator must realize the importance of a balanced design and large sample. ANOVA assumptions of normality and homogeneity of variances of the data distribution were checked. Figures 1 and 2 present the test of normality and linearity of the data.

Figure 1. Diagnostic Test of Normality and Linearity



According to Pallant (2007), a straight normal probability plot is an indication of normality and linearity. Pallant noted that when multiple regression assumptions are met, it produces a reliable result. From Figure 1 a reasonable straight line could be seen from the plot demonstrating normality and linearity of the data among the two variables (number of years in widowhood and the QoL of the widows). Alternatively, using the bell shape curve, Figure 2 gives the schematic of how a normal data should look like.

Figure 2. A Standard Normal Curve (Not from the Data Driven example)

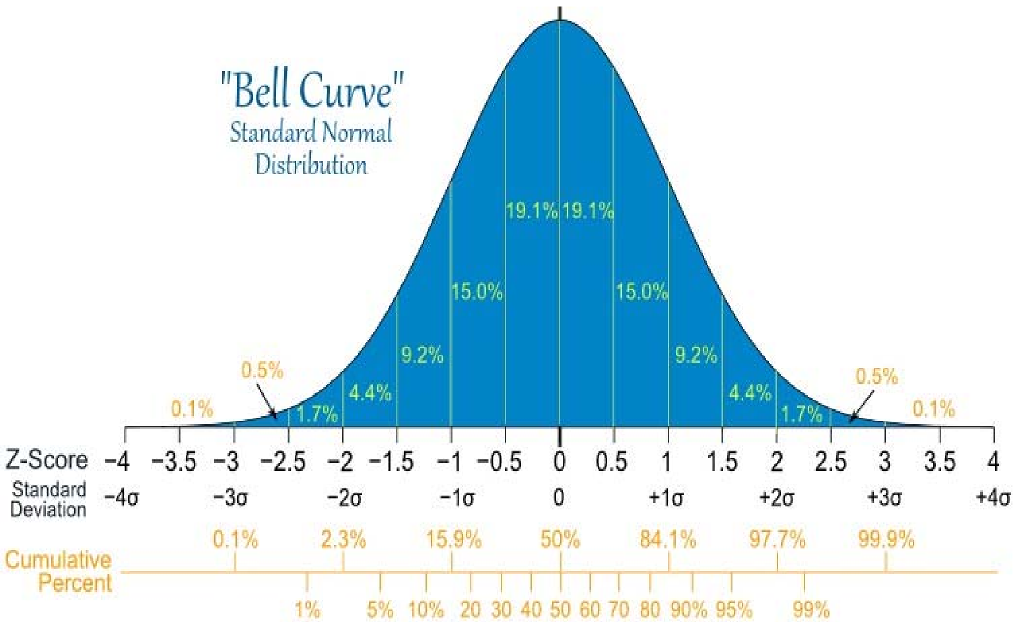
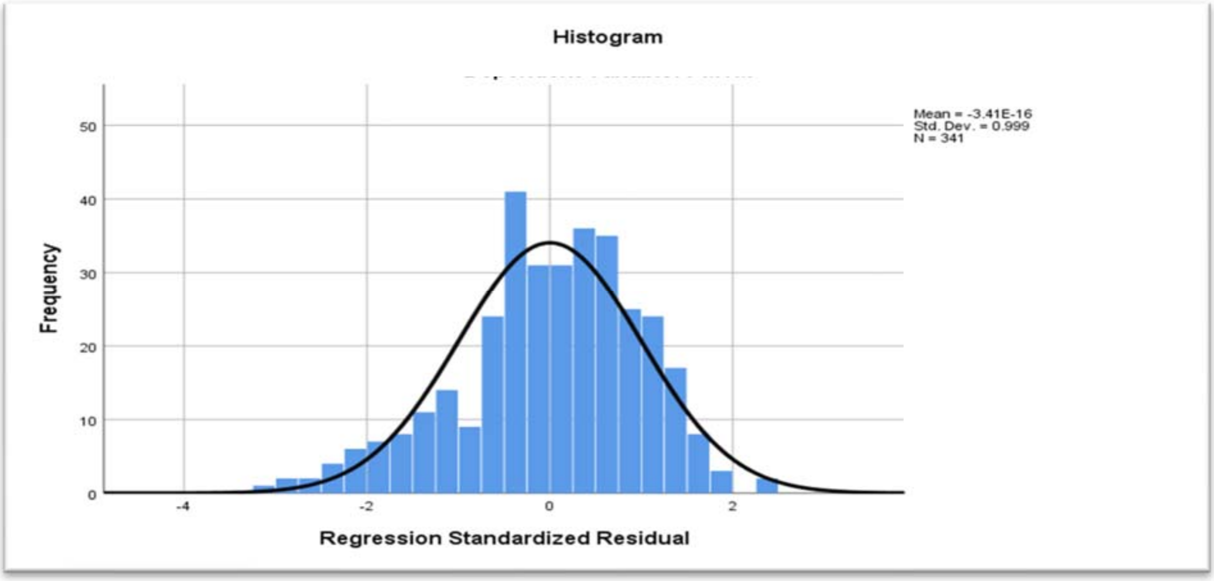
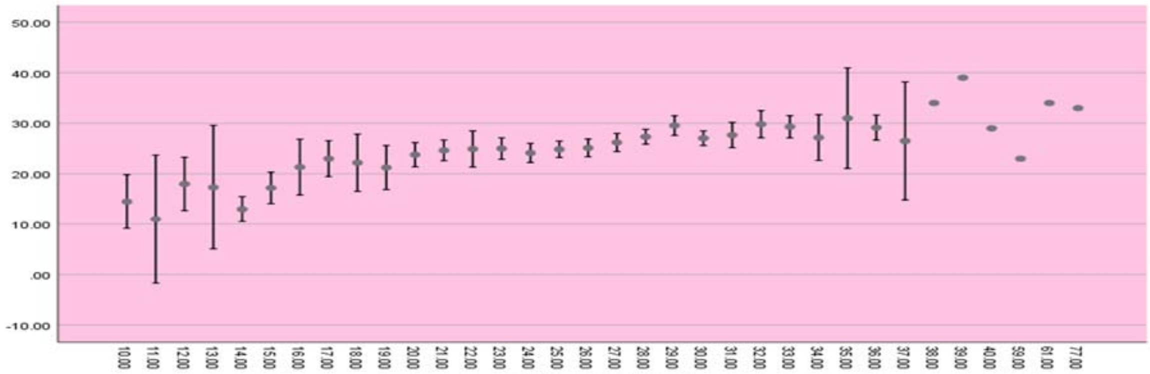


Figure 3. Histogram Test of Normality and Linearity (from the data driven example)



The Histogram plot of standardised predicted values versus standardised residuals, showed that the data met the assumptions of normality of variance and linearity and the residuals were approximately normally distributed.

Figure 4. Means Plot Test of Normality and Linearity



The Figure 4 presents results on the means plot test of normality and linearity. The results show that most of the bars are divided equally with few outliers which confirms that the data was assumed normal and as such the one-way analysis of variance (ANOVA) could be performed.

Table 2. Normality Test Results of the Variables (QoL* NYiW)

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
Age Ranges	Statistic	Df	Sig. value	Statistic	Df	Sig. value
1-3 years	.063	45	.206(ns)*	.865	45	.245(ns)*
4-6 years	.167	51	.445(ns)*	.295	51	.353(ns)*
7-10 years	.051	32	.230(ns)*	.143	32	.542(ns)*
11 years and above	.463	22	.270(ns)*	.191	22	.075(ns)*
Observations (sample)	150	150	150	150	150	150

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction
Source: Field Survey (2021) *Significant difference exists at p≤0.001, CI: 95%
Key: **ns***=not significant, **Df***= degrees of freedom, **Sig-V*** =Significant Value

In Table 2, Shapiro-Wilk test results are reported based on the assumption that it uses a sample size greater than 50 (n >50). Shapiro-Wilk test results are said to be normal if the sig value is greater than 0.001. From the

Shapiro-Wilk test results, it is indicated that the dependent variable (QoL) was normally distributed among number of years in widowhood. For example, widows within 1-3 years scored a Shapiro-Wilk indicating that it was normal *(SW = .865, df=45, p=.245**, p≤0.001, n=150, CI: 95%),* widows within 3 - 6yrs also recorded a Shapiro-Wilk results indicating that it was normal *(SW =. 295, df=51, p=.353**, p≤0.001, n=150, CI: 95%).* Also, widows within 8 years and above detailed a Shapiro-Wilk signifying that the data was normal *(SW = .191, df=22, p=.075**, p≤0.001, n=150, CI: 95%).* Upon testing for the normality of the data, the researcher proceeded to check whether the data variables were homogeneous. This therefore, means that conducting between-groups one-way analysis of variance (ANOVA) test was justified and statistically reasonable. The results are presented in Table 3.

Table 3. Results of Homogeneity of Variances Test (QoL* NYiW)

Test of Homogeneity of Variances					
		Levene Statistic	df1	df2	Sig. v(p-v)
QoL* NYiW	Based on Mean	.995	4	146	.411(ns)*
	Based on Median	.930	4	146	.448(ns)*
	Based on Median and with adjusted df	.930	4	145.521	.448(ns)*
	Based on trimmed mean	.995	4	146	.411(ns)*

Source: Field Data (2021) *Significant difference exists at p≤0.001, n=150, CI: 95%
*Key= **df1**=degrees of freedom one, **df2**= degrees of freedom two, **Sig-V*** =Significant Value, **ns***=not significant

Table 3 represents the test of homogeneity of variances of the study variables (number of years in widowhood and quality of life). From Table 3, using the based-on means, the homogeneity of variances test results specified that, assumption of homogeneity had not been violated *[t (df1=4, df2=146) = .995, Sig. value = .411, p≤0.001, 2-tailed, n=150, CI: 95%).)].* Performing of between-groups one-way analysis of variance (ANOVA) test was therefore, statistically justifiable and reasonable. Table 4 presents results on the descriptive statistics of the test (number of years in widowhood and QoL of the widows).

Table 4. Descriptive Statistics of the Study Variables (QoL* NYiW)

(QoL* NYiW)	n	M	Std. D	Std. Err	Ranking
11 years and above	22	58.7	4.190	.199	1st
7-10 years	32	37.9	5.712	.902	2nd
4-6 years	51	22.7	3.922	.703	3rd
1-3 years	45	16.7	6.130	.722	4th

Source: Field Data (2021) n=150
Key= n= sample Size, M*=Mean, St.D*= Standard Deviation St.D Err* = Standard Error*

The descriptive statistics as in Table 4 demonstrates that the differences existed in the mean scores of the ages of the number of years in widowhood and QoL of the widows. For example, widows in their 11 years and above recorded the highest mean *(M= 58.7, SD= 4.190, Std. Err=.199, n=22)* indicating that descriptively, widows in their 11 years and above were experiencing the highest quality of life. The descriptive statistics further indicated that those in their 7-10 years followed *(M= 37.9, SD= 5.712, Std. Err=.902, n=32).* Those in their early years (1-3 years) were found to be experiencing the least quality of life *(M= 16.7, SD= 6.130, Std. Err=.722, n=45, CI: 95%).* Nevertheless, the one-way analysis of variance (ANOVA) was conducted to establish more statistical evidence on whether the observed differences were not by chance. The ANOVA summary results is presented in Table 5.

Table 5. Summary of One-way Analysis of Variance (ANOVA) Results

Sources	Sum of Squares	Df	MS	F-value	Sig.V	Rks
Between Groups	1777.073	3	444.268	3.965	.0002(s)*	Diff.
Within Groups	41819.690	147	226.052			existed
Total	43596.763	150				

Source: Field Data (2021) *Significant difference exists at p≤0.001, n=150, CI: 95%
Key: **s***=significant, **Rks***=Remarks, **Sig-V***=Significant Value, **MS***=Mean Square, Df*=Degrees of freedom

A one-way Analysis of variance (ANOVA) was conducted to compare mean scores of the study variable (number of years in widowhood and QoL of the Widows). From the between-groups one-way analysis of variance (ANOVA) in Table 5, the results show that there was statistically significant difference in the number of years in widowhood and quality of life among young widows, *F (df1=3, df2=147) =3.965, p = .0002**, p≤0.001, n=150, 2-tailed, CI: 95%).* This gives statistical evidence to the effect that there were significant differences in mean scores of the number of years in widowhood and QoL of the Widows. From the ANOVA results, it is evident that the sig value (p-value) of 0.0002* (2-tailed) did not tell where the differences exist among the years in widowhood of the widows. Therefore, the Post Hoc test was conducted to find out the statistically significant differences between each pair of the years of the widowhood and their quality of life.

5. When the ANOVA Test is Significant, What Next?

When a researcher run an ANOVA, he or she is attempting to determine if there is a statistically significant difference between the groups that is not related to sampling error. If the researcher finds that there is a difference, he or she will then need to see between which of the groups the difference lays or where the differences are found among the independent variables (Naik & Reddy 2018; Zhou & Skidmore 2017). This is to mean that, all groups might be different, or perhaps only one of the groups are statistically different from the others. At this point, the researcher in question could run several *t*-tests to test the means between the groups, but this would not control for error as again you would be testing for several hypothesis at the same time. This test can be run using ANOVA multiple comparison test known as the post hoc test.

Post hoc comparisons (also called post hoc tests, multiple comparison tests, a posteriori comparison, and follow-up test or comparisons) are tests of the statistical significance of differences between group means calculated after ("post") having done an analysis of variance (ANOVA) that shows an overall difference. The F ratio of the ANOVA tells us that some sort of statistically significant differences exists somewhere among the groups being studied. Subsequent, post hoc, analyses are meant to specify what kind and where (Morgan *et al.* 2004; Brown 2005; Zhou & Skidmore 2017).

In testing this in ANOVA, there are several multiple comparison tests that can be conducted to control the type one error rate. If the researcher is concerned about violations of the assumptions use Scheffe's Test. If the researcher is not concerned about violations to the assumptions and are testing compound and pair wise tests, use Dunn's test or the modified Bonferroni Test. If the researcher is not concerned with violations of the assumptions and is just comparing the treatment to the control, use Dunnette's Test. If the researcher is not concerned with violations of the assumptions and is comparing all possible pair wise use Tukey's Test. If the researcher is not concerned with violations of the assumptions and is testing more than half of the possible pair wise comparisons again use Tukey's Test (Mrkvicka *et al.* 2016; Pohlert 2014; Kim 2014). If the researcher is not concerned with violations to the assumptions and are testing less than half of the possible pair wise comparisons, the researcher must use Dunn's Test or the modified Bonferroni Test. All of these tests will ensure that the Type I error rate remains under control and will tell the researcher exactly which groups are different from one another (Sow 2014; Pohlert 2014; Kim 2014). After meeting all the conditions and assumptions, Post-Hoc test was performed and the results are presented in Table 6.

Table 6. Post-Hoc Test among the Years in Widowhood and QoL

Games-Howell				
(I) Years in Widowhood	(J) Years in Widowhood	Mean Difference (I-J)	Std. Error	Sig. v (p-v)
1-3 years	4-6 years	-8.323*	.133	.0001(s)*
	7-10 years	-4.859*	.151	.0001(s)*
	11 years and above	-4.443*	.279	.0001(s)*
4-6 years	1-3 years	8.323*	.133	.0001(s)*
	7-10 years	3.464*	.186	.0001(s)*
	11 years and above	3.880*	.299	.0001(s)*
7-10 years	1-3 years	4.859*	.151	.0001(s)*
	4-6 years	-3.464*	.186	.0001(s)*
	11 years and above	.4157	.308	.0003(s)*
11 years and above	1-3 years	4.448*	.279	.0001(s)*
	4-6 years	-3.881*	.299	.0001(s)*
	7-10 years	-.4157	.308	.0003(s)*

*. The mean difference is significant at the p≤0.001 level, CI: 95%
Source: Field Data (2021)

Table 6 displays the result of the Post-Hoc test (Games-Howell). The Post-Hoc test shows where the differences among the years in widowhood and QoL. From the Post-Hoc test, there are significant differences between years in widowhood and QoL. For example, between 1-3 and 4-6 years, the mean difference and standard error of *(MD=-8.323*, SR= .133)* with a Sig value of 0.0001* (2-tailed) show that there was a difference in 1-3 years and 7-10 years, and the results are statistically significant. Further, between 1-3 and 11 years and above, the results show a significant difference (p-v=0.0001**) with mean difference and standard error of *(MD=-4.443*, SR= .279, CI: 95%).*

Discussion

Clearly, this paper introduces research practitioners on how to practically and conveniently use ANOVA in their studies. It is believed that a wide variety of approaches and explanatory methods are available for explaining ANOVA in different disciplines. However, illustrations in this manuscript were presented as a tool for providing an understanding to those who are dealing with primary social science data. Plethora studies have been conducted using ANOVA as a statistical tool however, with different or insufficient write up or reporting essentials (Zhou & Skidmore 2017; Yang 2019).

As similarly reported in this study, Kim (2017) also pointed out that ANOVA falls under the category of parametric analysis methods which perform the analysis after defining the distribution of the recruitment population in advance. Therefore, normality, independence, and equal variance of the samples must be satisfied for ANOVA. This suggest that the processes of verification on whether the samples were extracted independently from each other, Levene's test for determining whether homogeneity of variance must be satisfied, and Shapiro-Wilk or Kolmogorov test for determining whether normality should be satisfied and must be conducted prior to deriving the results (Kim 2017; Lee 2015; Cortina & Nouri 2017).

Most of the reporting rubrics or skills in this paper lend support to the work of Allen, Bennett and Heritage (2014) who in their study provided ANOVA guidelines for researchers. In their study, they share the ideas that the purpose of conducting an ANOVA is to determine whether the data show evidence opposed to this assumption about the null hypothesis. Therefore, claims of a true null hypothesis or claims of no differences among groups are incorrect. Statistical testing can be useful in helping us understand our data, but this does not work when they stand alone. These numbers and results need interpretation so the reader can better understand the purpose of these tests in relation to their findings (Beins 2021; Naik & Reddy 2018).

In the study of Yang (2019), it is similarly asserted when claiming that there were no differences, it can suggest that no further interesting data can be found. On the contrary, it should suggest that there is not enough information yet or methods of the given research can be improved. As a result, these results should lead to more analyses from different perspectives. The present reporting guidelines for ANOVA in the paper share similar ideas with the work of Field (2013), who asserted that in articles that do not address statistically significant results further than their significance, it could be difficult to understand the author's stance on their findings.

Relatedly, Nahm (2017) and Lee (2016) and Mrkvicka *et al.* (2016) in their studies reported that although in most the ANOVA assumptions could be met, however, the interpretations may be lacking and may not add to meaningful conclusions. The implication therefore, is that most researchers use statistical testing with no benefit and meaningful implication.

Concluding Remarks

As presented and illustrated in this paper, one-way ANOVA testing has a number of advantages and implications in educational research. In educational research, ANOVA puts all the data into one *F* number and gives one *p* to test the null hypothesis and the results are used for policy implications and theory development. Practically, ANOVA robustly controls for statistical errors so that the Type I error likelihood remains at 5% via its reduction of random variability thus ensuring confidence in its results. In using ANOVA in studies, researchers must be aware that not all dataset could be applicable in the test. As illustrated in the paper, it is practical and interesting to apply and analyze ANOVA in educational research if all the assumptions in datasets (variables) are met. Nonetheless, it must be stress that despite all of these benefits of ANOVA in educational research, it is instructive for educational researchers to note that, one-way ANOVA is not a perfect test and under certain circumstances will provide misleading results especially if all statistical assumptions are not taken into consideration.

Abbreviations

ANOVA: Analysis of Variance; **QoL:** Quality of Life; **NYiW**; Number of Years in Widowhood; **MD**: Mean Differences; SD: Standard Deviation; **Df**: Degrees of Freedom; **MS:** Mean Square; **ES**: Effect Size; ANCOVA: Analysis of Covariance; **SPSS**: Statistical Package for Social Sciences

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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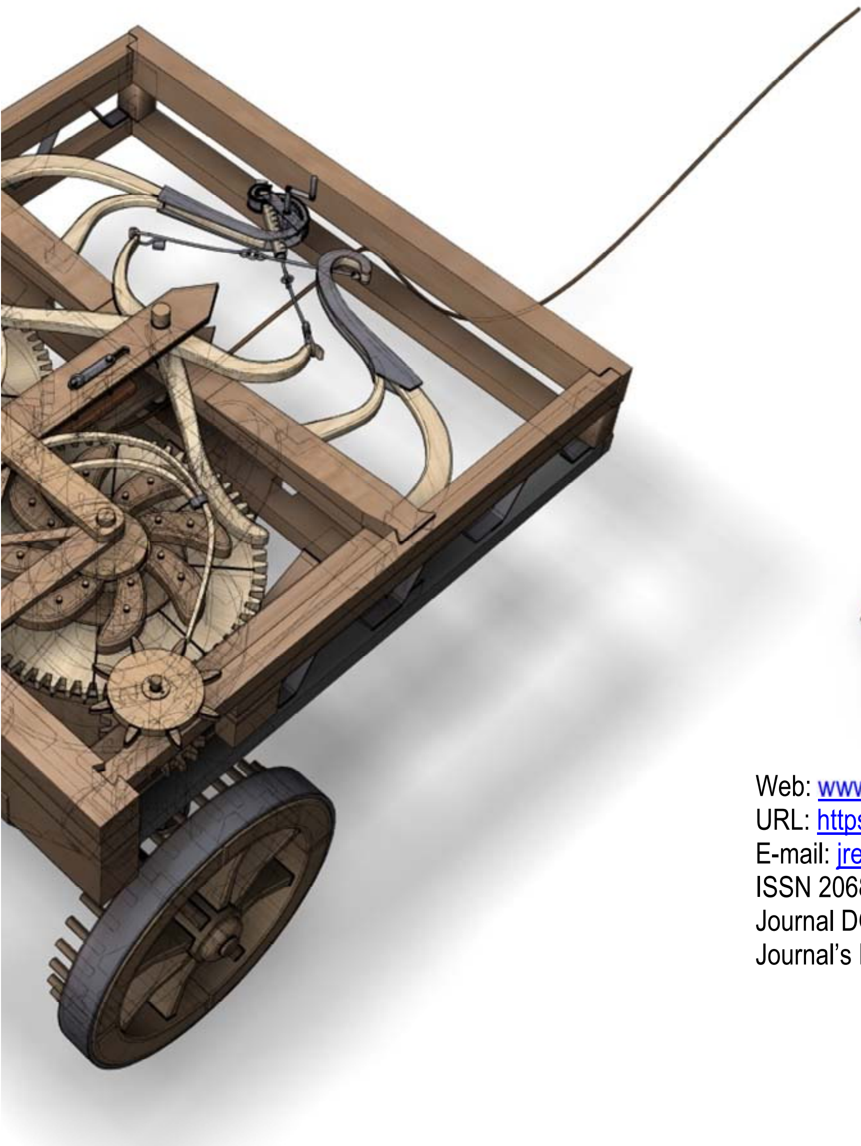

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