UNIVERSIDADE da MADEIRA
FACULDADE DE ARTES E HUMANIDADES

Guia de Investigação em Psicologia da Educação

Research Guide in Educational Psychology

Margarida Pocinho
Soraia Garcês

Título/Title: Guia de Investigação em Psicologia da Educação / Research Guide in Educational Psychology

Autores/Authors: Margarida Pocinho & Soraia Garcês

Composição gráfica/Graphic Composition: Soraia Garcês

Data de Publicação/Publication Date: dezembro/December 2019

Disponível em/Available at: https://digituma.uma.pt/

ISBN: ***978-989-8805-60-7***

Publicado em Portugal pela Universidade da Madeira. / Published in Portugal by University of Madeira.

Morada/Address: Campus Universitário da Penteada, 9020-105 Funchal, Portugal.

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Chapter 8

Introdução

Este livro pretende ser um pequeno guia para a realização de alguns procedimentos estatísticos em investigação, particularmente no âmbito da Psicologia da Educação. Muitas vezes, quando procuramos realizar investigação quantitativa sentimos dificuldade e desistimos. O SPPS é um software estatístico imensamente utilizado; contudo sentimo-nos várias vezes assoberbados com tantos comandos e direções e com tantas tabelas e números obtidos através dos outputs. Neste sentido, este guia é como que uma primeira tentativa de compilar um conjunto de dicas que possam auxiliar a realização de análises estatísticas que são frequentemente utilizadas nas ciências sociais. Não somos experts em matemática ou ciências estatísticas, somos apenas entusiásticas da estatística e do SPSS em particular. Por isso mesmo, este livro representa alguns anos de estudo, investigação e leitura sobre estes tópicos que apesar de muitos considerarem complicados, nós consideramo-los importantes para melhorar e aumentar a investigação científica e rigorosa na disciplina científica da Psicologia da Educação.

As autoras,

Margarida Pocinho

Soraia Garcês

Introduction

This book aims to be a small guideline to perform some important statistics in scientific research, particularly in Educational Psychology. Many times, when looking at how to perform quantitative research we get stuck in how to do it and quit. SPSS software is massively used; however, we are many times overwhelmed with the many commands and directions it is possible to go and worse with the many tables, numbers that an output can show. Thus, this small guideline is a somewhat first attempt in giving tips to perform some statistics' analyses that are rather frequent in social sciences. We are not of any kind experts in mathematics or statistical sciences, we rather are enthusiastic about statistics and SPSS in particular. So, this book highlights some years of study, research and reading about these topics that while many considered a very much complicated endeavour, we considered it an important knowledge to improve and increase scientific and rigorous research in Educational Psychology.

By the Authors,

Margarida Pocinho

Soraia Garcês

Chapter 1

Effect Size

This chapter aims to explain effect size for the t-student test and ANOVA.

t **de Student effect size**

As Shields (2019, p.32) stated “Cohen's *d* is defined as the difference between two means divided by a standard deviation for the data”. Table 1 presents the descriptors for magnitudes of *d* = 0.01 to 2.0, as was firstly suggested by Cohen and then extended by Sawilowsky (2009).

Table 1

Effect size magnitudes

Effect size	*d*
Very small	.01
Small	.20
Medium	.50
Large	.80
Very large	1.20
Huge	2.0

(Sawilowsky, 2009)

Other authors choose a somewhat different calculation of the effect size such as Hedges' *g*, or Glass's *delta*.

Example of results with an internet calculator:

Cohen's *d* = (5.08 - 5.39)⁄1.470544 = 0.210806.

Glass's *delta* = (5.08 - 5.39)⁄1.43 = 0.216783.

Hedges' *g* = (5.08 - 5.39)⁄1.46982 = 0.21091.

ANOVA effect size η^2

The effect size with ANOVA (Analysis of Variance) is different from other tests such as the *t*-test. When calculating the effect size with ANOVA, it is used the Eta squared (η^2), instead of, for example, the Cohen's d with the t-test. But prior to see how to perform the effect size with ANOVA it is important to consider Cohen's (1988) cut-offs. For this author:

- Small: .01
- Medium: .059
- Large: .138

Chapter 2

Reliability or Internal Consistency

This chapter brings an overall guide and understanding about reliability also known as internal consistency of a given measure. We will be emphasizing Cronbach's alpha as this is one of the most widely used reliability measures.

What is Cronbach's alpha?

Cronbach's alpha, α (or *coefficient alpha*) measures reliability, or internal consistency. **Reliability** can be defined as how well a test measures what it should be testing ("Statistics How to", n.d.). For example, a school might decide to evaluate stress levels on its teachers. If reliability is high this means that we are measuring stress levels, however if reliability is low it means that we are possibility measuring something different that is not stress.

Cronbach's alpha allows to test if instruments with multiple items and with responses given through Likert scales are reliable. These items are trying to assess what is known as latent variables, which are variables that we could not see such as: an individual motivation, creativity or stress. This kind of variables are very hard to measure in real life. Through Cronbach's alpha we can now if our instrument is truthfully measuring our variables ("Statistics How to", n.d.).

Step by Step guide:

1. To obtain the Alpha first you need to go to “Analyze”, next go to “Scale” and choose “Reliability Analysis”.
2. Select the items that you want to look for reliability”.
3. Go to “Statistics” and in there choose, at least, “Item”, “Scale,” and “Scale if item deleted”.
4. Next choose “Correlation”, click “Continue” and finally “Ok”.

Usually when interpreting Cronbach’s Alpha, it is used a qualitative description to a better comprehension of the obtained values as can be seen in. Table 3. However, typically, a result > than .7 is considered okay (“Statistics How to”, n.d.).

Table 3

Cronbach’Alpha qualitative description

Cronbach Alpha (α)	Qualitative Description
≥ .90	Excellent
.90 > α ≥ .80	Good
.80 > α ≥ .70	Acceptable
.70 > α ≥ .60	Questionable
.60 > α ≥ .50	Poor
.50 > α	Unacceptable

(“Statistics How to”, n.d.)

Chapter 3

Exploratory Factor Analysis

This chapter aims to be a quick guide to understand the fundamental steps of how to perform an Exploratory Factor Analysis (EFA) through SPSS.

An EFA is a method that allows to understand if a group of items have some underlying common aspects that allows to group them in factors. Thus an EFA permits to analyse the structure of an instrument and its potential to measure a given construct or constructs.

Step by step guide:

1. First and foremost, regarding **sample size** Comrey and Lee (1992) suggested that 300 is a good number to perform an EFA.

2. Observe the value of the **Kaiser-Meyer-Olkin (KMO) test**.

- An acceptable value to proceed with the EFA is >.06 (Pestana & Gajeiro, 2008).
- **Bartlett's test** should be significant, <.05 (Field, 2009).

3. Factor loadings should be supressed for a cut-off of .60.

- According to Matsunaga (2010), a cut-off of .40 is marginally acceptable, and above .60 or .70 is more reliable. According to Tabachnik and Fidell (2007) >.71 is excellent; >.63 very good; >.55 good; >.45 sufficient; and >.32 is low.

4. **Method**. Preferably choose Principal Component Analysis.
    - There are different methods to look for underlying factors. Principal component analysis is usually used and "is concerned only with establishing which linear components exist within the data and how a particular variable might contribute to that component." (Field, 2009, p.638).

5. **Rotation** allows the items to load maximally to a factor and thus facilitating interpretation (Field, 2009).
    - Varimax rotation. Assumes that the factors are independent or not correlated (Field, 2009).
    - Oblique rotation. Assumes that the factors may be correlated. (Field, 2009)

6. When analysing the outputs, it is important to **consider**:
    - The table regarding individual items analysis. Can alpha improve if an item is eliminated? How are the item-total correlations? Does it make sense? Do you see the need to remove items?

    - **Explained variance** results. Observe the overall value and the emerged factor(s) values. Are they ok? In social sciences a number close to 50% is considered good.

    - **Scree plot**. Observe when the graphic line stabilizes, that's the number of factors that should be retained according to the scree plot. This method to retain factors can be used with more than 200 cases (Field, 2009).

- Observe the **Kaiser Criteria** where eigenvalue above 1 are considered to retain factors. How many factors emerged? Do they make sense? Is the number of factors to be retained similar to the scree plot?

Note 1. All your decisions should consider if it has theoretically support.

Note 2. If you retrieved any item at this point, next you should redo the EFA and observe again the above topics.

7. You can also **force the EFA** to a certain number of factors.
    - This means that theoretically, if it makes sense to do it, or after observing the Kaiser criteria or scree plot, you may decide that a certain number of factors should be retain, and so you can choose how many factors to retain.

Overall, when performing and EFA you have to look for the above steps and decide the best course of action depending on what is the aim of your EFA.

When you have a final structure next you should analyse reliability and if it is ok this structure should next be tested through a Confirmatory Factor Analysis.

Chapter 4

Confirmatory Factor Analysis

This chapter aims to present the basic steps to perform a Confirmatory Factor Analysis (CFA). An CFA, simply speaking, aims to test a model structure. It is “uma mistura de análise fatorial e análise de regressão, que permite aos pesquisadores testar estruturas fatoriais de instrumentos de medida psicométrica, por meio da análise fatorial confirmatória” (Pilati & Laros, 2007, p.205-206). It uses latent variables (that cannot be observe directly) and observable variables (for example: scale items).

To perform a CFA it is important that the measure used to retrieved data have a good psychometric quality and a solid theoretical model (Pilati & Laros, 2007, p.207). Adding Pilati and Laros (2007, p.209-210) that “As relações que serão construídas pelo pesquisador entre as variáveis devem ser embasadas em pressupostos teóricos e evidências empíricas anteriores. Essa característica é essencial para que o pesquisador possa alcançar resultados teoricamente coerentes e modelos ajustados aos dados”.

What to know before: (Byrne, 2010; Pilati & Laros, 2007, p.208).

1. Relationships between variables are represented by path diagrams.
2. Observable variables are represented by rectangles or squares.
3. Latent variables are represented by circles or ellipses.
4. To each observable variable there is an associated error.

5. Relationships are made through unidirectional or bidirectional arrows

Important assumptions:

- Univariate and multivariate normality.
- No missings (Pilati & Laros, 2007, p.209-210)].

Goodness-of-fit indices:

- Normed Chi-squared (χ^2/df) < 2 with a non-significant *p-value*;
- RMR (*Root Mean Square Residual*) ≤ .05;
- GFI (*Goodness of Fit Index*) > .90;
- AGFI (*Adjusted Goodness of Fit Index*)> .90;
- CFI *Comparative Fit Index*)> .90;
- RMSEA (*Root Mean Square Error of Approximation*) ≤ .05

(Byrne, 2010; Pilati & Laros, 2007; Schumacker & Lomax, 2004; Ulman 2007)

Modification Indices (MI)

The MI give the expected value that chi-square will diminished if a certain parameter is added to the model (Schumacker & Lomax, 2004).

MI can be added to the initial model to improve it. However, to do it, it is important to have a theoretical reason to change the initial model (Pilati & Latos, 2007).

Step by step guide

1. You need a **prior structure** model to test and its database.
2. To run a CFA you need a sample of at least 200 subjects.
3. Design/represent the model in AMOS.
4. Add the individual items from the scale(s) used to each observable variable you created in the graphic model.
5. Introduce the **errors**.
6. Add arrows for the relationship between variables that may exist.
7. Run the analysis (calculate the estimates).
8. Look for the **goodness of fit indices**.
9. If everything is ok your model is good to go.
10. If not, you can add **modification indices (MI)**.
11. When using MI, each time one is introduced in the model run the analysis and look for goodness of fit indices.
12. You cannot introduce MI between errors from different factors.
13. It is also possible to improve the model by analysing the standardized residuals covariances and eliminating the items that are problematic.

Chapter 5

MANOVA/MANCOVA

This chapter aims to present the basic steps of how to perform a MANOVA and a MANCOVA. First, we will start with a MANOVA which can be seen as an extension of an ANOVA. MANOVA stands for Multivariate Analysis of Variance and is mainly used when we want to test several dependent variables. When wanting to test various variables it is better to perform a MANOVA than many ANOVAs (Field, 2009). According to Field (2009, p. 586) "MANOVA has greater power to detect an effect, because it can detect whether groups differ along a combination of variables whereas ANOVA can detect only if groups differ a single variable".

To perform a MANOVA some assumptions are needed (Field, 2009):

- Independence
- Random sampling
- Multivariate normality (done by analysing univariate normality of each dependent variable)
- Homogeneity of covariances matrices/equality of variances

Step by step guide

1. Choose your **independent variable**s (fixed factor) and your **dependent variables**.
2. Test **normality**.

3. Test **equality of variances**

   - You can run **Levene test** that should not be significant for any of the dependent variables (Field, 2009).

   - Use **Box's test**. This test should also be non-significant. However, if sample sizes are equal there is no need for this test since Hotelling and Pillai's are considered robust. But if sample sizes are different robustness is not assumed. (Field, 2009)

4. **Choose a test**.

   - When sample sizes are equal the Pillai test is the most robust. But when samples are different this test is affected by violations of the assumption of equal covariances. Thus, when you have different sample sizes you should use Box's test. This means that Box's test should be non-significant and if multivariate normality is ok, then **Pillai's trace** test is considered accurate (Field, 2009).

5. Run the analysis. Are there any significant results?

   - If so report them, look for its variance and run ANOVAS to each of the dependent variable (Field, 2009)

6. If you want to look for possible variables affecting the interactions between independent and dependent variables you may introduce covariates (If they are continuous variables). This will lead you to perform a MANCOVA (Multivariate Analysis of Covariance)

How to perform a MANCOVA:

1. So, to do a MANCOVA, introduce a continuous variable in the model as a covariate.
2. Look for **Box's M value** which should be again non-significant.
3. Look and see if the **model is significant or not**.
   - If before this analysis the model was significant and after introducing a covariate is still significant it may indicate that the covariate is not controlling the interaction. However, you should look for F-values and partial eta square. If there is any change in them you should further analysed the univariate effects. If something changes, for example, if new significant results show up, it may mean that your covariate is a "confounding variable".
   - If the model was not significant and now it is, so your covariate is important since it is having an interaction effect.

Chapter 6

Regression

This chapter will present how to perform a regression analysis and further on a Logistic Regression. Regression analysis allows to predict a certain outcome from one or more predictors. If we introduce just one predictor we are talking about a simple regression. If we introduce more than one predictor (independent variables) it is called a multiple regression (Field, 2009; Tabacknick & Fiddel, 2007). So, in a simple linear regression you have the following equation (Field, 2009):

$$Yi = (b0 + b1Xi) + \varepsilon i$$

While in multiple regression you have this kind of equation (Field, 2009):

$$Yi = (b0 + b1Xi1 + b2Xi2 + . . . + bnXn) + \varepsilon i$$

- Y_i = dependent or outcome variable (DV)
- b_1, b_2,…b_n, =regression coefficients associated to the predictors or independent variables
- b_0 = constant
- ε_i, = random error (Field, 2009).

- If an independent variable significantly predicts an outcome (DV), the values of b_1,b_2,…b_n, should be significantly different than 0. If they are significant the predictor contributes significantly for the DV estimation (Field, 2009), which means that if the *t* test value associated to the value of $b_1, b_2, \ldots b_n$ is significant, the predictor significantly contributes to the model (Field, 2009).

What you need to know before performing a Regression:

- You need enough data to follow a regression analysis and thus for it to be considered a reliable model.

- **Minimal N** numbers can be found through the following formulas, where m is the number of independent variables (IV):
    - $N \geq 50+8m$, this formula allows to test for multiple correlation;
    - $N \geq 104+m$, this formula allows to test for the individual predictors (Tabacknick & Fiddel, 2007).

Analysis of the *goodness of fit*

To interpret a regression it is crucial to analyse the goodness of fit, which means how well the model that we have adjusts to our data. For this, look for:

- **R^2** - is the proportion of variance of the dependent variable explained by the model.
- **F** - for a good model, this should be a high value, at least higher than 1 (Field, 2009).

Step by step guide

1. Choose your **dependent** and **independent variables** (for a simple or multiple regression).

2. Choose a **regression method**:

- **Hierarchical (Blockwise entry)**. "Predictors are selected based on past work and the experimenter decides in which order to enter the predictors into the model. As a general rule, known predictors (from other research) should be entered into the model first in order of their importance in predicting the outcome" (Field, 2009, p. 212).

- **Forced entry (Enter or standard)**. All chosen variables enter simultaneously in the model, which is advised when we are theory testing (Field, 2009).

- **Stepwise method.** The computer choses the variable with the best variance to explain the model, then looks for the next, and continues on. It retains only those who contribute significantly. But in this method, it also makes a removal test for the predictor that is least important (Field, 2009).
  - **Forward method.** The computer choses the variable with the best variance to explain the model, then looks for the next, and continues on. It retains only those who contribute significantly.
  - **Backward method.** The computer puts all predictors at once and then looks for its significance, if a predictor is not significant for the model it is removed.

- It is better for you to choose the backward method instead of the forward method.

- The stepwise methods bring the danger of over-fitting (many variables that bring little contributions for the DV) and of under-fitting (letting out an important predictor of the model). Therefore, they are not recommended, only for exploratory model building (Field, 2009).

What should you do next?

1. Observe **R^2**, **F**, and any **significant results**. Do you have found a significant model?
   - If yes, how well the model fits the data?
2. To see **how well the model fits the data**:
   - Look for **outliers** through residuals analysis. General rule standardized residuals with an absolute value > 3.29 (or close to 4) can be problematic and is probably and outlier.
   - Look for **influential cases** through Cook's distance. Values > 1 are a problem. However, if we have a significant outlier but Cook's distance is <1 there is no need to eliminate because it does not have a big influence on the regression analysis (Field, 2009).

- If the model fits the data you can try to see if it can be **generalized** beyond your sample. For this some **assumptions need to be met** and after **a cross-validation is also needed** for you to be able to generalize the model.

Assumptions:

- All predictors must be **quantitative or categorical**, and the DV must be quantitative.
- **No multicollinearity**. Predictors should not have high correlations between them. For this you can use the *variance inflation fator* (VIF), which should be <10 and *Tolerance >.1* and if possible >.02 (Field, 2009).
- **Homoscedasticity**, which means that for each predictor the residuals variance should be constant. For this analysis you can look the ZRESID vs ZPRED graphic (Field, 2009), which should be a set of points distributed randomly and uniformly around the value zero. If the graphic makes some kind of pattern it probably means there is heterocedasticity of data. If it makes some kind of curve there is a violation of the linearity assumption, which is also necessary for the generalization of the model. (Field, 2009).
- **Independent errors or no autocorrelation.** You can test it with the Durbai-Watson test. Values close to 2 mean that the residuals are not correlated. Values <1 or >3 are a concern.
- **Normal distribution of errors.** Use the *normal probability plot* to verify this assumption or the Kolmogorov-Smirnov test to the standardized residuals. (Field, 2009).

3. If after all of this everything is ok, you can see how well your model fits other samples. For this you can use the **adjusted R^2**:

  - SPSS calculates the adjusted R^2 through the **Wherry's equation** which has been criticized.

- A new way of achieving the adjusted R^2 uses **Stein formula** (Field, 2009).

$$adjusted\ R^2 = 1 - \left[\left(\frac{n-1}{n-k-1}\right)\left(\frac{n-2}{n-k-2}\right)\left(\frac{n+1}{n}\right)\right](1-R^2) \quad (2)$$

- **R^2** = unadjusted value
- ***n* =** number of subjects
- ***k* =** number of predictors/independent variables

- When the result through Stein formula is similar to the results of SPSS, **cross-validation** looks good (Field, 2009).

And how to perform a Logistic Regression?

First, according to Field (2009, p.265) “logistic regression is multiple regression but with an outcome variable that is a categorical variable and predictor variables that are continuous or categorical. In its simplest form, this means that we can predict which of two categories a person is likely to belong to given certain other information.”

When you only have two categorical predictors it is used the **binary logistics regression**, but when you have more than two you called **multinomial logistic regression**.

The logistic regression equation (Field, 2009):

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i})}}$$

In logistic regression it is predicted the probability of Y occur considering the values of X (Field, 2009).

- P(Y) = probability of Y occurring
- e=base of natural logarithms
- b0 = constant
- X1= predictor
- B1=coefficient/weight

It is possible to have an equation with multiple predictors (Field, 2009):

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} + \ldots + b_n X_{ni})}}$$

Looking for Model fit:

- Observe the **Log-likehood**. High values mean a poor fit. You can compare the log-likehood of different models and see the difference between them (Field, 2009).
- Observe the **R-statistic** which varies between -1 and 1. Small values of R mean that it contributes very little for the model.
- Look for the **Wald statistics** which is similar to the regression coefficients and uses the chi-square distribution. If Wald is significant, the predictor is contributing to the model.
- Observe **Odds ratio [Exp (B)]**. When values are >1 “then it indicates that as the predictor increases the odds of the outcome occurring increase.

Conversely, a value less than 1 indicates that as the predictor increases, the odds of the outcome occurring decrease" (Field, 2009, p.268)

Choose a Method:

- **Forced entry (Enter)**. All predictors enter at the same time.

- **Forward stepwise.** The computer starts with the constant and adds predictors, one by one, that are most significant. It also sees if some should be eliminated. This is possible through 3 ways (Field, 2009):
    - **Likehood ratio statistics**. The computer compares the model with and without the predictors.
    - **Conditional.** Similar to the above, so it is better to use the above.
    - **Wald statistics**. Any predictors with significant values (>1) are removed.

- **Backward method.** It starts with all predictors and the computer tests to see if any must be out of the model to fit the data better.

- Again, backward is better as is the likehood ratio statistics (Field, 2009).

For Logistic Regression some assumptions are needed:

- **Linearity**. Can be seen in "the interaction term between the predictor and its log transformation is significant" (Field, 2009, p.273).
- **Independence of errors**. Cases should not be related.

- **Multicollinearity**. Predictors should not be highly correlated and it can be observed through tolerance and VIF.

More:

- Observe the **-2log-likehood statistics** and the **chi-square value**, if it is <.05, the model significantly fits the data.
- Look for the variables that **significantly predict the IV** in the Table Variables in the equation and see **those who don’t** in the Table Variables not in the equation.
- Look for the **Wald statistics and its significance**, which should be <.05.
- Look for the **Exp (B)** if >1 as the predictor increases the odds also increase, when <1 when the predictor increases, the odds decrease (for this the confidence interval should not pass 1) (Field, 2009).

- **Multinomial logistic regression** functions similarly to the binary logistics regression

Chapter 7

Others: Convergent validity -Average Variance Extracted (AVE) and Composite Reliability (CR)

In this chapter we aim to present some other important procedures that can be helpful when analysing data through structural equation modelling.

To analyse convergent validity of a given measure **Average Variance Extracted (AVE)** can be used, when a variable is able to explain at least half of the variance of its items (Bagozzi & Yi, 1988). To acknowledge convergent validity AVE must be >.50 (Fornell & Larcker,1981; Sharma, 1996; Ahmad, Zulkurnain & Khairushalimi, 2016). However, to perform an AVE a structural equation model must already exist (Verial, nd).

For a complementary or alternative measure of reliability other that Cronbach's alpha, **Composite Reliability (CR)** can be used. For this analysis, values should be >.70 (Bagozzi & Yi, 1988).

Following Fornell and Larcker (1981) if AVE is <.50, but composite reliability is >.60, we can say that the convergent validity of the concept is adequate.

Chapter 8

Reporting Statistics

This chapter aims to be a quick guide to how to report some statistics.

1. Cronbach's Alpha

- You should report the number of items that are part of the instrument and the obtained value of the Cronbach's alpha.

Examples:

- The Cronbach's alpha for the 8 items of the Tourism Wellbeing Scale was .83 and for the Creative Personality Scale was .85.
- The CPS was found to be highly reliable (9 items; $\alpha = .85$).
- Reliability of the original study was .87 and in the current research internal consistency was .85.

2. Correlations

- You should report the correlation (r) and the significance level (*p*).

Examples

- A Pearson' r correlation coefficient was performed to measure the relationship between creativity and wellbeing. A strong positive correlation was found between the two variables [.154<r <.204, p <.05]. Increases in levels of creativity were correlated with increases in participants wellbeing.

- Creativity and Optimism were significantly correlated, r = .65, p<.05.
- There was a nonsignificant correlation of .06 (p = .05) between creativity and intelligence average.

3. Regression

- You should report the R^2, F value, degrees of freedom, significance level (p), beta (β) and also the corresponding t-test for each of the predictors.

Example

- Multiple regression analysis was used to test if the creativity traits significantly predicted participants' ratings of wellbeing. Results of the regression analysis indicated that the 2 predictors explained 25.6% of the overall variance (R^2=.26, F(3,43)=6.43, p<.05). It was found that creativity significantly predicted wellbeing (β = .73, p<.05).

4. t-Tests

- You should report the mean (M) and standard deviation (SD) for each group you are analysing and also the t value (t), degrees of freedom, and significance level (p).

Example

- Men (M = 2.7, SD = .25) showed significantly higher values of wellbeing than women (M = 2.20, SD = .15), t(2) = 4.33, *p* < .05. Women (M = 2.05, SD = .30) and men (M = 2.11, SD = .23) did not differ significantly on creativity, t(3) = 2.12, *p* = .08.

5. ANOVA's

- You should report the mean (M) and standard deviation (SD) for each group you are analysing and also the F value, degrees of freedom and significance level (*p*).

Examples

- The effect of the academic degree was non-significant, F(5, 34) = 4.43, *p* = .45. Participants with high school, bachelor and master did not differ on the self-esteem levels.
- An effect of year the academic degree was found for wellbeing, F(2, 54) = 15.22, *p* <.01. High school (M = 2.34, SD = .55) and master participants (M = 3.05, SD = .32) showed significantly higher wellbeing than did the bachelor participants (M = 1.23, SD = .20).

6. MANOVA/MANCOVA

- You should report the V (Pillai Trace), F value, significance level (*p*) and the partial eta square ($\eta p2$).

Example:

- "Using Pillai's trace, there was a significant effect of therapy on the number of obsessive thoughts and behaviours, $V = 0.32$, $F(4, 54) = 2.56$, $p < .05$. However, separate univariate ANOVAs on the outcome variables revealed non-significant treatment effects on obsessive thoughts, $F(2, 27) = 9.73$, $p > .05$, and behaviours, $F(2, 27) = 5.23$, $p > .05$" (Field, 2009, p. 615).

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Лариса Головата