

Controlling false positive rates in research and its clinical implications

Rafael Simas¹, Felipe Maestri², David Normando³

Statistical analysis is, in fact, an error analysis. A statistical test does not guarantee reliable results, it only quantifies the probability of error of a given conclusion.¹ While reading the articles of this journal, you will find a p-value. For instance, the article by Garib et al² describes the p-values for a given variable at two different moments: this p-value, also known as false-positive rate,¹ demonstrates the probability of error when asserting that there is a difference before and after expansion.

Every research is subjected to some degree of error, given that we are not investigating an entire population, but only a fraction, a sample. For this reason, when we compare two samples undergoing different treatment procedures with a view to identifying the most efficient therapy, we will always have the chance of having reached a wrong conclusion. Therefore, the lower the p-value is, the smaller the chance of error and, as a result, the more certain we are to assure that treatment “A” is more efficient than “B”.

But, how can we control a false-positive error? Initially, we have to decide on the significance level (α) we expect to establish. In Dentistry, we usually set a significance level not greater than 5% ($\alpha = 5\%$). Nevertheless, should we increase the number of comparisons of a given study, we increase the chances of yielding outcomes that are due just to chance and, as a consequence, finding a false-positive result. The lottery is a good example. The chances of winning are little, less than 5%. However, the more we bet, the higher our chances of winning.

In statistical tests, there is a dramatic increase in false-positive rates, in which the number of comparisons is directly proportional to the number of false-positive results, as shown in Table 1.

Thus, when we make several comparisons using a simple statistical test, we significantly increase the chances of yielding a false-positive result. Table 1 demonstrates that the chances of yielding a false-positive result are of 40% for a study involving 10 comparisons. In these cases, some adjustments are necessary to keep the significance level set at 5%. One of the procedures employed to correct false-positive rates is the Bonferroni correction. It consists of dividing the significance level by the number of comparisons made in a given study.³ Suppose we carried out a comparative analysis of five cephalometric variables between two groups using an independent t-test. By dividing the significance level initially set at 0.05 or 5% by 5, the new level of error will be adjusted to 0.01 or 1%. Thus, differences will be considered significant for a p-value lower than or equal to 0.01. Nevertheless, Bonferroni correction

Table 1. Number of comparisons (tests) and increase in false-positive rates.

# tests	α value	FW α
1	0.05	0.05
3	0.05	0.14
6	0.05	0.26
10	0.05	0.4
15	0.05	0.54

$$\alpha_{w} = 1 - (1 - \alpha_{pc})^c$$

C = # of comparisons. α_{pc} stands for error type I (0.05).

How to cite this article: Simas R, Maestri F, Normando D. Controlling false positive rates in research and its clinical implications. *Dental Press J Orthod.* 2014 May-June;19(3):24-5. DOI: <http://dx.doi.org/10.1590/2176-9451.19.3.024-025.ebo>

¹ Masters student in Dentistry, Federal University of Pará.

² Specialist in Orthodontics, Brazilian Dental Association – Southern Maranhão.

³ Professor, School of Dentistry, Federal University of Pará.

Submitted: Mach 05, 2014 - **Revised and accepted:** March 20, 2014

Contact address: Rafael Simas

David Normando

Rua Boaventura da Silva, 567-Ap. 1201.

CEP 66055-090 - Belém-PA — Brazil

E-mail: davidnormando@hotmail.com

results in a much more inflexible significance level than necessary, thus increasing the chances of yielding a false-negative rate.⁴

In 1995, Benjamini and Hochberg⁵ (BH) suggested another method to counteract false-positive rates when multiple comparisons with univariate statistical analysis are carried out. In this procedure, the researcher has to accept a minor false-positive rate and set this rate before the procedure. Suppose we compared 10 cephalometric measures between two populations A and B. After the number of comparisons is established, we determine the p-value for each analysis and organize these values in ascending order. The value of $i = 1$ (0.01) will be lower than the p-value, with $i = 10$ being the highest value. Table 2 shows the p-values in ascending order. After values are properly ranked, we apply the Benjamini-Hochberg formula: $(i/m) \cdot Q$ (Q = false-positive acceptance rate; m = total number of comparisons). This formula allows us to correct the p-value and eliminate potential false-positive rates. With a view

to obtaining the Q value, we divide the number of comparisons with $P < 0.05$ by the number of comparisons with $P > 0.05$. Table 3 shows that after finding the Q value and applying the Benjamini-Hochberg formula, we find the corrected p-value for each comparison ($i = 1, i = 2$, etc.). Subsequently, we arrange the data in a table similar to Table 3, including the initial p-value and the p-value corrected by means of the formula. This method allows us to determine which comparisons are significant, in which case only those with a p-value lower than $[(i/m) \cdot Q]$ are significant.⁶ Table 3 shows that comparisons 1 and 2 are the only ones with p-value lower than $[(i/m) \cdot Q]$.

In this same example, should we use Bonferroni correction to counteract error type I, comparisons 1 and 2 would probably not be significant, since $\alpha = 5\%$ divided by the number of comparisons (ten) would result in $0.05/10 = 0.005$. This value would be lower than comparisons 1 and 2 corrected by the BH technique, which demonstrates how strict Bonferroni's procedure is.

Choosing the wrong statistical test may lead clinicians to jump to conclusions. For instance, a given treatment may be considered the best one as a result of statistical analysis. Thus, statistical analysis is the key to reach more reliable clinical results. Employing more simple statistical procedures, such as the t-test, to carry out multiple comparisons, creates the need to counteract type I error (false-positive). Therefore, it is reasonable to conclude that multiple comparisons require one to carefully choose the test as well as the corrections to be employed.

Table 2.

Comparisons	P-value
$i = 1$	0.01
$i = 2$	0.017
$i = 3$	0.2
$i = 4$	0.22
$i = 5$	0.23
$i = 6$	0.3
$i = 7$	0.35
$i = 8$	0.4
$i = 9$	0.45
$i = 10$	0.5

Table 3.

Comparisons	P-value	$(i/m) \cdot Q$
$i = 1$	0.01	0.025
$i = 2$	0.017	0.05
$i = 3$	0.2	0.075
$i = 4$	0.22	0.1
$i = 5$	0.23	0.125
$i = 6$	0.3	0.15
$i = 7$	0.35	0.175
$i = 8$	0.4	0.2
$i = 9$	0.45	0.225
$i = 10$	0.5	0.25

$Q = 2/8 = 0.25$.

REFERENCES

1. Normando ADC, Almeida MAO, Quintão CCA. Análise do emprego do cálculo amostral e do erro do método em pesquisas científicas publicadas na literatura ortodôntica nacional e internacional. *Dental Press J Orthod.* 2011;16(6):33.e1-9.
2. Garib DG, Menezes MHO, Silva Filho OG, Santos PBD. Immediate periodontal bone plate changes induced by rapid maxillary expansion in the early mixed dentition; CT findings. *Dental Press J Orthod.* 2014 May-June;19(3):36-43.
3. Chen JJ, Roberson PK, Schell MJ. The false discovery rate: a key concept in large-scale genetic studies. *Cancer Control.* 2010;17(1):58-62.
4. McDonald JH. *Handbook of biological statistics.* 2nd ed. Baltimore: Sparky House; 2011. p. 256-9.
5. Benjamini Y, Hochberg Y. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society.* 1995; 57(1):289-300.