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HYPOTHESIS TESTING AND STATISTICAL TEST SELECTION: FUNDAMENTALS OF STATISTICS IN CLINICAL STUDIES – PART II

TESTIRANJE HIPOTEZE I IZBOR STATISTIČKOG TESTA: OSNOVE STATISTIKE U KLINIČKIM ISTRAŽIVANJIMA – DEO II

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Summary
Hypothesis testing is a systematic procedure for evaluating assumption about difference or relationship between variables. This process involves four main steps: formulating a hypothesis, establishing decision-making criteria, calculating statistical values, and drawing a conclusion. In clinical studies, the process begins with the formulation of a hypothesis, which includes both the alternative and null hypothesis. Statistical tests are employed to assess the null hypothesis by calculating key statistical values, such as the test statistic and p-value. Based on the p-value, conclusions are made regarding the presence of a significant difference or relationship between the variables under study. The selection of an appropriate statistical test depends on various factors, and understanding these factors is crucial for making valid inferences and accurately interpreting clinical study results. This professional article outlines the steps involved in hypothesis testing and discusses the key considerations for selecting the appropriate statistical test.
Key words: Research Design; Models, Statistical; Statistics as Topic; Data Interpretation, Statistical

Sažetak
Testiranje hipoteze je sistematski postupak u kome se proverava pretpostavka o razlici ili vezi između varijabli. Može se razložiti u četiri koraka: postavljanje hipoteze, određivanje kriterijuma za donošenje odluke, izračunavanje statističkih veličina, te donošenje odluke odnosno zaključka. Klinička istraživanja započinju postavljanjem hipoteze, koja ima dva oblika: alternativni i nulti. Statistički testovi proveravaju nultu hipotezu i izračunavaju statističke veličine (statistiku testa i p-vrednost). Na osnovu p-vrednosti se donosi zaključak o postojanju razlike ili veze između varijabli. Izbor statističkog testa zavisi od nekoliko faktora a njihovo poznavanje je neophodno za donošenje validnih zaključaka i ispravno tumačenje rezultata kliničkog istraživanja. Ovaj stručni rad opisuje korake u testiranju hipoteze i faktore koji su od značaja za izbor odgovarajućeg statističkog testa.
Ključne reči: dizajn istraživanja; statistički modeli; statistika kao tema; statistička interpretacija podataka

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Introduction

Clinical studies enhance our understanding of the etiology, diagnosis, prevention, prognosis, treatment, and outcome of diseases. These studies are conducted under specific conditions defined by the study design, inclusion and exclusion criteria, variables to be measured, and other parameters. However, these conditions do not perfectly reflect real-life scenarios, as real-life conditions cannot be precisely defined [1]. Despite this, clinical studies aim to simulate real-life as closely as possible, making it crucial to select a sample that is representative of the target population (e.g., children, women, patients with diabetes). In practice, the entire population is rarely accessible, and even in smaller populations, it is nearly impossible to recruit all individuals within it [1, 2].

After sampling, subjects are classified into groups and monitored by measuring various variables. The results of these measurements are then generalized to the entire population based on the inferences drawn through hypothesis testing [2].

Statistical inference, or hypothesis testing, involves four main steps: formulating a hypothesis, establishing decision-making criteria, calculating statistical values from the sample data, and drawing a conclusion or inference [3]. For instance, in a ran-

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Abbreviations

COVID-19	– Corona Virus Disease of 2019
H_0	– null hypothesis
ND	– normal distribution
RM	– repeated measurements
ANOVA	– analysis of variance

domized controlled trial, it was hypothesized that preoperatively administered liraglutide would reduce the number of cardiac surgery patients requiring intraoperative insulin for glycemic control [4]. A decision-making criterion was established (α=0.05), what will be discussed later. The chi-square test was used to evaluate the hypothesis and compute statistical values (χ^2 and p-value). Based on the p-value, a conclusion was made regarding the acceptance of the hypothesis [4].

This professional article outlines the steps involved in hypothesis testing and discusses the key factors relevant for selecting the appropriate statistical test.

Null Hypothesis, Type I error, Type II error, and Test Power

Clinical studies, particularly randomized controlled trials, begin with the formulation of one or more hypotheses to be tested [1]. A hypothesis is an assumption regarding a difference or relationship between two or more variables, and it can take two forms: the alternative hypothesis and the null hypothesis. The alternative hypothesis posts that there is a significant difference between the variables. In contrast, the null hypothesis assumes the opposite: there is no significant difference between the variables, and any observed difference is due to chance [1, 3].

Although the focus is on the alternative hypothesis, statistical testing is conducted on the null hypothesis. The process begins with the assumption that the null hypothesis is true, and efforts are made to gather evidence to reject it. The alternative hypothesis is not directly tested; it is automatically accepted as true if there is sufficient evidence to reject the null hypothesis [2, 3].

When testing a null hypothesis, there are four possible outcomes: two correct and two incorrect [1, 3]. An inference is correct if the true null hypothesis is accepted or if the false null hypothesis is rejected. Conversely, an inference is incorrect if the true null hypothesis is rejected (Type I error) or if the false null hypothesis is accepted (Type II error). A Type I error is a false positive, where it is incorrectly inferred that there is a difference between two variables when there is actually no difference. The probability of committing a Type I error is denoted by the significance level α. A Type II error is a false negative, where it is incorrectly concluded that there is no difference between two variables when a difference does exist. The probability of committing a Type II error is denoted by β [1, 3, 5, 6] **(Table 1)**.

The power of a test is related to the Type II error and it is calculated 1-β. By definition, it is the probability that the test will detect a difference or relationship in the sample when such a difference or relationship actually exists in the population [1, 3, 5, 6]. Tests with low power may fail to identify a statistically significant difference or relationship; conversely, excessively high test power may lead researchers to overstate the significance of a statistical difference or relationship beyond what is justified by clinical practice [6].

There is a trade-off between Type I and Type II errors: reducing α increases β, and vice versa. Ideally, both α and β should be 0%, but this is unattainable due to sampling variability, which is an inherent part of any clinical study. Consequently, by convention, α is typically set at 5%, and β at 20% or 10% [1]. This implies that 5% probability of a false positive and a 20% or 10% probability of a false negative are deemed acceptable. Accordingly, the acceptable power of a test is 80% or 90%.

P-value

A statistical test computes a test statistic and the associated p-value. Based on the p-value, an inference is made about whether to accept or reject the null hypothesis [1, 3, 5, 6]. The p-value, representing the computed level of statistical significance, is compared with the predetermined level of statistical significance (α). If the p-value is less than α, the null hypothesis is rejected; conversely, if the p-value is equal to or greater than α, the null hypothesis is accepted. For example, α is conventionally set to 0.05. This means that if the p-value is less than 0.05, the null hypothesis is rejected because it is unlikely that the observed difference between the variables is due to chance. Conversely, if the p-value is equal to or greater than 0.05, the null hypothesis is accepted because it is highly likely that the observed difference between the variables is due to chance [1, 3, 5, 6]. Therefore, the p-value is conceptually related to α, it is not the same as α.

Choosing a statistical test

There are numerous statistical tests, and those commonly used are listed in **Tables 2 and 3** [7–10].

Table 1. Four inferences in the null hypothesis testing
Tabela 1. *Četiri zaključka kod testiranja nulte hipoteze*

	True H_0/*Tačna H_0*	False H_0/*Netačna H_0*
Fail to reject H_0 /*H_0 se ne odbacuje*	Correct inference/*Ispravan zaključak*	Type II error/*Greška tipa II*
Reject $H_{0//}$*H_0 se odbacuje*	Type I error/*Greška tipa I*	Correct inference/*Ispravan zaključak*

Legend: H_0 – null hypothesis/*Legenda*: *H_0 – nulta hipoteza*

Table 2. Statistical tests employed to test the difference between variables [6, 7, 10, 13].
Tabela 2. *Statistički testovi koji se koriste za ispitivanje razlike između varijabli [6, 7, 10, 13].*

Dependent variable *Zavisna varijabla*			Independent variables *Nezavisne varijable*			
Scale of measurement *Skala merenja*	ND *NR*	RM *PM*	Measurements (N) *Merenja* (N)	Number *Broj*	Groups (N)* *Grupe* (N)*	Statistical test *Statistički test*
Quantitative *Kvantitativna*	Yes *Da*	No *Ne*	1	1	2	Unpaired Student's t-test *Neupareni Studentov t-test*
Ordinal, quantitative *Ordinalna, kvantitativna*	No *Ne*	No *Ne*	1	1	2	Mann-Whitney U-test *Man-Vitnijev U-test*
Quantitative *Kvantitativna*	Yes *Da*	No *Ne*	1	1	≥3	One-way ANOVA *Jednofaktorska ANOVA*
Ordinal, quantitative *Ordinalna, kvantitativna*	No *Ne*	No *Ne*	1	1	≥3	Kruskal-Wallis test *Kruskal-Volisov test*
Qualitative *Kvalitativna*	–	No *Ne*	1	1	≥2	Chi-square test *Hi-kvadrat test*
Quantitative *Kvantitativna*	Yes *Da*	Yes *Da*	2	1	2	Paired Student's t-test *Upareni Studentov t-test*
Ordinal, quantitative *Ordinalna, kvantitativna*	No *Ne*	Yes *Da*	2	1	2	Wilcoxon's rank test *Vilkoksonov test ranga*
Quantitative *Kvantitativna*	Yes *Da*	Yes *Da*	≥3	1	≥3	Paired one-way ANOVA *Uparena jednofaktorska ANOVA*
Ordinal, quantitative *Ordinalna, kvantitativna*	No *Ne*	Yes *Da*	≥3	1	≥3	Friedman's test *Fridmanov test*
Dichotomous *Dihotomna*	–	Yes *Da*	2	1	2	McNemar's test *Maknemarov test*
Dichotomous *Dihotomna*	–	Yes *Da*	≥3	1	≥3	Cochran's Q test *Kohrejnov Q test*

*Two and three groups in statistical tests with repeated measurements are time 1/time 2 and time 1/time 2/time 3, consequently.
**Dve i tri grupe u statističkim testovima sa ponovljenim merenjima su vreme 1/vreme 2 i vreme 1/vreme 2/vreme 3, redom.*
Legend: ND – normal distribution; RM – repeated measurements; ANOVA – analysis of variance
Legenda: NR – normalna raspodela; PM – ponovljena merenja; ANOVA – analiza varijanse

The choice of an appropriate test depends on several factors, including the study hypothesis, the scale of measurement for the dependent variable, the distribution shape of the dependent variable, the number of measurements of the dependent variable, and the number of independent variables along with their scales of measurement [6, 10].

Study hypothesis

The first factor to consider when choosing a statistical test is the study hypothesis, which can involve an assumption about a difference or a relationship between two or more variables. When testing a hypothesis about a difference (e.g., therapy outcomes differing between two groups of patients), the guidelines given in **Table 2** should be followed. Conversely, when testing a hypothesis about a relationship (e.g., a relationship between patient age and cardiovascular events), the guidelines given in **Table 3** should be followed.

Scale of measurement for the dependent variable

Another crucial factor to consider in selecting a statistical test is the scale of measurement for the dependent variable. This requires an understanding of nominal, ordinal, interval and ratio scales. Generally, nominal and ordinal scales are classified as qualitative, while interval and ratio scales are classified as quantitative [3]. Variables measured on a quantitative scale can be categorized, though this is not always ideal due to the potential loss of information. For instance, when assessing the effect of age on the risk of a cardiovascular event, younger individuals typically have a lower risk than older individuals. A researcher may decide to categorize the age into groups such as <18 years, 18-44 years, 45-64 years, and ≥65 years. However, this categorization results in a loss of detailed information, as the exact age of each subject becomes obscured. For example, a 44-year-old is considered the same as an 18–year-old since they fall into the same category, but they are treated differently from a 45-year-old who falls into a different category.

Distribution shape for the dependent variable

Statistical tests can be categorized as parametric and nonparametric [5, 7]. The choice between these depends on the distribution shape of the quantitative dependent variable. Parametric tests, such as Student's t-test, analysis of variance (ANOVA), and Pearson's correlation, are used when the distribution is normal **(Tables 2 and 3).** When there is a significant deviation from normal distribution, or when

Table 3. Statistical tests employed to test the relationship between variables [6, 7, 10, 13]
Tabela 3. *Statistički testovi koji se koriste za ispitivanje veze između varijabli [6, 7, 10, 13]*

	Dependent variable *Zavisna varijabla*		Independent variables *Nezavisne varijable*		
	Scale of measurement *Skala merenja*	ND *NR*	Number *Broj*	Scale of measurement *Skala merenja*	Statistical test *Statistički test*
Correlation *Korelacija*	Qualitative *Kvalitativna*	–	1	Qualitative *Kvalitativna*	Chi-square test or Fisher's exact test *Hi-kvadrat test ili Fišerov test*
	Quantitative *Kvantitativna*	Yes *Da*	1	Quantitative *Kvantitativna*	Pearson's correlation *Pirsonova korelacija*
	Ordinal, quantitative *Ordinalna, kvantitativna*	No *Ne*	1	Ordinal, quantitative *Ordinalna, kvantitativna*	Spearman's correlation *Spirmanova korelacija*
Regression *Regresija*	Quantitative *Kvantitativna*	Yes *Da*	1	Quantitative or qualitative *Kvantitativna ili kvalitativna*	One-way linear regression *Jednostavna linearna regresija*
	Quantitative *Kvantitativna*	Yes *Da*	≥2	Quantitative or qualitative *Kvantitativna ili kvalitativna*	Multivariable linear regression *Višestruka linearna regresija*
	Dichotomous *Dihotomna*	–	1	Quantitative or qualitative *Kvantitativna ili kvalitativna*	Simple logistic regression *Jednostavna logistička regresija*
	Dichotomous *Dihotomna*	–	≥2	Quantitative or qualitative *Kvantitativna ili kvalitativna*	Multivariable logistic regression *Višestruka logistička regresija*
Agreement *Slaganje*	Qualitative/*Kvalitativna*	–	0	–	Cohen kappa/*Koenova kapa*
	Quantitative *Kvantitativna*	Yes *Da*	0	–	Intraclass correlation coefficient *Intraklasni koeficijent korelacije*

Legend: ND – normal distribution/*Legenda*: *NR – normalna raspodela*

the dependent variable is measured on an ordinal or nominal scale, nonparametric tests, such as Mann-Whitney U-test, Kruskal-Wallis test, Friedman's test, and Spearman's correlation, are employed **(Tables 2 and 3).** Generally, parametric tests have greater power than nonparametric tests to detect differences if they exist.

Testing the normality of distribution can be done using visual methods (distribution curve, Q-Q plot), measures that describe distribution shape (skewness and kurtosis), and statistical significance tests (e.g., Kolmogorov-Smirnov test, Shapiro-Wilk test) [11]. A normal distribution curve is symmetrical, bell-shaped, and has the mean, median, and mode nearly identical. A Q-Q plot indicates normal distribution if the data points lie along a diagonal line. Numerically, a distribution is considered normal if skewness and kurtosis values are zero, although values ranging between -2 and +2 are also acceptable [12]. The Kolmogorov-Smirnov test is commonly used to test normality, indicating a normal distribution if the computed p-value is above 0.05 [13].

Apart from normal distribution, variables can have a positively skewed distribution (most values are low) or a negatively skewed distribution (most values are high). Since parametric tests require normally distributed variables, the question arises about how to handle variables with asymmetric distribution. One option is to use nonparametric tests as an alternative to parametric tests [10, 13]. Another option is to transform variables that do not follow a normal distribution [10, 13]. Depending on the original distribution shape (positive or negative skewness), various mathematical transformations (e.g., square root, logarithm, inversion) can be applied to approximate normality [13]. For negatively skewed distribution, the data is first reflected to produce a positively skewed distribution before applying the appropriate transformation. There is a considerable debate in the literature regarding the transformation of variables; some researchers support it, while others against it due to the challenging interpretation of transformed variables and availability of nonparametric counterparts to most parametric tests, which do not rely on distribution assumptions.

Number of measurements of the dependent variable

A dependent variable can be measured once, twice or multiple times. When measurements are repeated, the values of one variable may influence the values of another, resulting in paired dependent variables [10]. For instance, Hemmati et al. examined the impact of physical activity on the immune system of patients after kidney transplantation [14]. The immune condition was assessed based on the cytokine profile, determined before the study and at week 12, upon completion.

Dependent variables are also considered paired when subjects are included in the study as pairs based on age, sex, clinical characteristics, or similar factors, with each subject in a pair exposed to different intervention [13]. For example, Feldman et al. compared the effects of different inhaled medications on clinical outcomes, measured by hospitalization rates and exacerbations in chronic obstructive pulmonary disease [15]. A matched cohort study included 30,216 pairs of subjects, where one subject in each pair used a long-acting muscarinic agonist/

long-acting beta-adrenergic agonist combination, and the other used an inhaled corticosteroid/long-acting beta-adrenergic agonist combination.

The number of measurements of the dependent variable is crucial when choosing the appropriate version of a statistical test. For example, the Student′s t-test has different versions or mathematical approaches depending on whether the dependent variable is measured once (unpaired Student′s t-test) or twice (paired Student′s t-test) **(Table 2)** [10]. The paired Student′s t-test was used in the study by Hemmati et al. [14].

Number of independent variables and their scale of measurement

When selecting a statistical test, it is essential to consider the number of independent variables, their scale of measurement, the number of groups (categories) of the independent variable, and whether there is an interaction between the independent variables [10]. Notably, the distribution shape of the independent variable is never a consideration in statistical analyses [10].

The number of independent variables is crucial when choosing a test for regression analysis **(Table 2).** For example, Awan et al. examined the relationship between spasticity and constipation in children with cerebral palsy [16]. Since spasticity was the sole independent variable, its relationship with constipation was tested using simple linear regression. In contrast, Qiao et al. included several independent variables, such as metabolic parameters (e.g., free fatty acids, triglycerides, total cholesterol, glucose, insulin), and tested their relationship with weight gain using multiple linear regression [17].

As for the scale of measurement, analysis of variance and regression analysis are mathematically equivalent [10]. However, analysis of variance is used when the independent variables are qualitative, whereas regression analysis can handle both qualitative and quantitative independent variables **(Tables 2 and 3).**

Study design can include one, two, three, or more groups. With only one group, comparisons are not possible, so descriptive statistical methods are used instead [2, 10]. For example, Montenegro et al. conducted a cross-sectional study among primary care patients with post COVID-19 to describe symptoms and prevalence using descriptive statistics such as mean and standard deviation for quantitative data (e.g., duration of symptoms) and percentage for qualitative data (e.g., prevalence of symptoms) [18]. In studies with two groups, an appropriate statistical test for comparison is required. For instance, Pajić et al. studied the characteristics of seizures in childhood acute gastroenteritis, dividing patients into febrile and afebrile group and comparing their characteristics (e.g., age) using the Student′s t-test, which compares means between two groups [19]. For studies with more than two groups, the statistical analysis becomes more complex. All groups are compared simultaneously using the appropriate test, and if a statistically significant difference is found, post hoc tests determine the significance of the differences between specific pairs of groups. For example, Akinbade et al. compared the effectiveness of analgesics on pain after surgical tooth extraction by randomizing patients into three groups (ibuprofen, celecoxib, and tramadol) and comparing the mean pain intensity scores using one-way ANOVA [20]. Since the test indicated a statistically significant difference ($p = 0.0039$), the post hoc tests were used to identify which pairs of groups differed significantly.

An interaction occurs when one independent variable affects another. In multiple linear regression, high correlation between independent variables (correlation coefficient ≥ 0.9) negatively impacts test quality. Therefore, it is advisable to exclude one of the highly correlated variables from the analysis or to combine them into a single independent variable [13].

Conclusion

Hypothesis testing involves four key steps: formulating a hypothesis, establishing decision-making criteria, calculating statistical values (test statistic and p-value) from the sample data, and drawing a conclusion or inference. The choice of an appropriate statistical test depends on several factors, including the study hypothesis, scale of measurement for the dependent variable, distribution shape, number of measurements of the dependent variable, number of independent variables, and their scales of measurement. A thorough understanding of these factors is essential for drawing valid inferences and correctly interpreting the results of clinical studies.

References

1. Poropat G, Milić S. Slučajne pogreške u istraživanjima i važnost veličine uzorka. Medicina Fluminensis. 2017;53(4):473-9.

2. Ranganathan P, Pramesh CS. An introduction to statistics: understanding hypothesis testing and statistical errors. Indian J Crit Care Med.2019;23(Suppl 3):S230-1.

3. Spasić S, Kotur-Stevuljević J, Bogavac-Stanojević N. Primenjena statistika za studente farmacije. Beograd: Farmaceutski fakultet; 2020.

4. Hulst AH, Visscher MJ, Godfried MB, Thiel B, Gerritse BM, Scohy TV, et al. Liraglutide for perioperative management of hyperglycaemia in cardiac surgery patients: a multicentre randomized superiority trial. Diabetes Obes Metab. 2020;22(4):557-65.

5. Hazra A, Gogtay N. Biostatistics series module 2: overview of hypothesis testing. Indian J Dermatol. 2016;61(2):137-45.

6. Popović J, Nikolić B, Popović K, Milošević N, Popović D. Statistika u kliničkim istraživanjima – interpretacija rezultata. In: Popović J, editor. Statistički principi u kliničkoj farmaciji. Novi Sad: Medicinski fakultet; 2021. p. 1-64.

7. Ranganathan P. An introduction to statistics: choosing the correct statistical test. Indian J Crit Care Med. 2021;25(Suppl 2):S184-6.

8. Sebastião YV, St Peter SD. An overview of commonly used statistical methods in clinical research. Semin Pediatr Surg. 2018;27(6):367-74.

9. Kebalepile MM, Chakane PM. Commonly used statistical tests and their application. Southern African Journal of Anaesthesia and Analgesia. 2022;28(5 Suppl 1):S80-4.

10. Walters RW. The application of statistical analysis in the biomedical sciences. In: Malone PM, Malone MJ, Witt BA, Peterson DM, editors. Drug information: a guide for pharmacists. 7th ed. New York: McGraw Hill; 2022. p. 289-396.

11. Cooksey RW. Descriptive statistics for summarising data. In: Cooksey RW. Illustrating statistical procedures: finding meaning in quantitative data. 3rd edit. Singapore: Springer; 2020. p. 61-139.

12. Milošević Z, Bogdanović D. Statistika i informatika u oblasti medicinskih nauka. Niš: Galaksija, Medicinski fakultet; 2012.

13. Pallant J. SPSS Survival Manual. 7th ed. London: Routledge; 2020.

14. Hemmati N, Kazemi S, Jamshidian-Tehrani N, Roozbeh J, Koushkie Jahromi M, Salesi M, et al. Effects of exercise training on immunological factors in kidney transplant recipients: a randomized controlled trial. Res Sports Med. 2022;30(1):80-91.

15. Feldman WB, Avorn J, Kesselheim AS, Gagne JJ. Chronic obstructive pulmonary disease exacerbations and pneumonia hospitalizations among new users of combination maintenance inhalers. JAMA Intern Med. 2023;183(7):685-95.

16. Ahmet Awan W, Masood T, Kanwal R. Effectiveness of physical therapy for improving constipation in spastic cerebral palsy. Altern Ther Health Med. 2021;27(S1):185-9.

17. Qiao Q, Bouwman FG, van Baak MA, Roumans NJT, Vink RG, Mariman ECM. Plasma levels of triglycerides and IL-6 are associated with weight regain and fat mass expansion. J Clin Endocrinol Metab. 2022;107(7):1920-9.

18. Montenegro P, Moral I, Puy A, Cordero E, Chantada N, Cuixart L, et al. Prevalence of post COVID-19 condition in primary care: a cross sectional study. Int J Environ Res Public Health. 2022;19(3):1836.

19. Pajić J, Redžek Mudrinić T, Kavečan I, Vijatov Đurić G, Milanović B, Vorgučin I. Febrile and afebrile seizures associated with mild acute gastroenteritis in childhood. Med Pregl. 2022;75(5-6):166-70.

20. Akinbade AO, Ndukwe KC, Owotade FJ. Comparative analgesic effects of ibuprofen, celecoxib, and tramadol after third molar surgery: a randomized double blind controlled trial. J Contemp Dent Pract. 2018;19(11):1334-40.

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