International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

Experimental Designs and Statistics: An Overview of Multidisciplinary Applications

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Abstract: ***This article offers a comprehensive review of experimental design methodologies and their statistical underpinnings across diverse scientific domains. It examines classical models such as Randomized Blocks, Latin Squares, Split Plots, and Nested Designs, discussing their core principles, advantages, and limitations. The paper highlights how these methodologies address challenges like heterogeneity and missing data, enhancing research quality. Through multidisciplinary examples from engineering, healthcare, agriculture, and education, the study underscores the adaptability and critical importance of experimental designs in contemporary research.***

Keywords: Experimental design, Statistical analysis, Randomized block design, Missing data, Multidisciplinary research

1. Introduction

People have always been interested in the events and objects around them. This interest varies in degree and level from person to person. Therefore, people have always been interested in conducting experiments and utilizing the results of those experiments. Thus, the concepts of experimentation and research have gained common ground. When planning experiments, the goal is to obtain the most reliable results in the shortest time and at the lowest cost. However, it is not always possible to achieve these goals. The accuracy of the results obtained is made possible by the application of statistical methods.

The most important aspect of scientific research is the planning, execution, and conclusion of the research using scientific methods. Research that is not based on scientific objectives may not be useful and may even produce harmful results. For this reason, the applicability of experimental studies must always be determined by the validity of statistical methods.

In recent years, developments in computer technology have made significant contributions to the creation of effective experimental designs and the computational and interpretive techniques used to analyze the data obtained from these designs [1]. These developments have become an important tool in meeting the needs of those working in the fields of science, engineering, health, and agricultural research [2]. The techniques used demonstrate the same usefulness in different scientific disciplines with practical applications.

Every experimental research problem requires the selection of a unique experimental design [3]. In this selection, it is appropriate to choose the simplest design that can meet the requirements of the experimental studies. In modern experimental design models, three basic principles (replication, randomization, and blocking) and the relationships between them are taken into account. These principles were developed by R.A. Fisher and his colleagues and are the most important concepts to consider in effective experimental designs [4]. According to Fisher, in order to calculate experimental error, the experiment must be repeated and the subjects must be completely randomly assigned to the experimental units. Without these conditions, the experimental error cannot be calculated correctly.

In addition to the measures taken in experimental design, increasing the number of repetitions reduces experimental error. Considering the research areas used, the problems to be addressed, and the strengths and weaknesses of each design will provide significant benefits to the researcher [5]. These insights are particularly timely, given the growing reliance on data-driven methodologies and the demand for reproducible and efficient research practices across disciplines. Relevant literature reviews are current studies between 2019 and 2025, and evaluations have been made for studies belonging to different scientific fields.

2. Experimental Designs and Statistical Analysis

In this section, the characteristics of experimental design models, their areas of application, and their uses in different fields are explained with examples.

2.1 Randomize Block Design

Randomized block design is one of the most preferred experimental designs in field trials and other agricultural research [6]. It is widely used, especially when the aim is to examine the effect of two different factors on the dependent variable. For example, it is preferred in studies where the effects of fertilizer types and soil types on productivity must be evaluated together. In such cases, the factors contribute to the results not only through their individual effects but also through their combined effects. This combined effect is defined as "interaction" in the literature. Additionally, this method makes variance analysis more economical and meaningful.

In field experiments, the experimental area is divided into multiple blocks of equal size and similar characteristics. The number of blocks is determined to be equal to the number of replicates conducted. Each block is divided into plots of equal size corresponding to the number of treatments. For example, if there are t treatments and r replicates, r blocks are formed, each consisting of t plots. Thus, the experiment is conducted on a total of t × r plots. This design is suitable for cases where heterogeneity in the field exists along a single axis, which this design aims to reduce. Blocks are considered homogeneous within themselves, and this approach is expected to yield more reliable results.

In randomized block designs, apart from the effect of the treatments being tested, there may be cases where observation values cannot be obtained from some experimental units for various reasons. In such cases of missing observations, the relevant observation value is estimated using the missing observation formula. The following formula is used for this purpose:

$$\hat{X} = \frac{b.B + mM - G}{(b-1)(m-1)} \quad (1)$$

In the above formula; $B:$ is the sum of the other elements in the block with missing observations, $M:$ is the sum of the other observations in the treatment with missing observations, $b:$ is the number of blocks, $m:$ is the number of treatments, and $G:$ is the sum of the observation values belonging to other experimental units. If there are more than one missing observations, estimation is performed using average values in place of all but one of the missing observations. This process continues until the estimated value remains unchanged. Here, the degrees of freedom for the missing observation are adjusted by subtracting one from the total sum of squares for the general and error terms. The model equation for the randomized block design is as follows.

$$Y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij} \quad (2)$$

Where Y_{ij} is the observation value from treatment i in block j. The observation value from process i in block j., μ is the overall mean, τ_i is the effect of process i. The effect of transaction i (fixed effect), β_j is the effect of block j, and ε_{ij} is the error term (random, $N(0,\sigma^2)$ distribution). The main purpose of the randomized block design is to collect data and ANOVA is used to examine the differences between the data.

2.1.1 Advantages and Disadvantages of Random Block Design

It is known that random blocks have a highly compatible structure in experimental design. Since differences between blocks can be attributed to experimental error, it is not necessary for the blocks to be physically adjacent to each other [7]. Even if a repetition or an observation value for a subject cannot be obtained, no significant difficulties arise in terms of statistical analysis. However, as blocks grow larger, processes such as block folding becomes necessary due to greater material variability between plots within the same block. When there are a large number of subjects, the "Incomplete Blocks Experimental Design" is preferred. This design offers a highly balanced and easy-to-calculate structure, as each block contains all of the experimental subjects.

This experimental design ensures more accurate results compared to random plot distribution by grouping plots into blocks. There is no fundamental limitation on the number of subjects and blocks. If additional repetition is required for some subjects, it can be applied to multiple plots. Analysis can be performed even if there is a loss of observation in a block or specific subjects. In the event of a few missing plots, the Missing Plots method can be used to resolve the issue. However, if the number of missing observations increases significantly or becomes widespread across different blocks, this design is considered less tolerant than the Random Plots design [8]. Additionally, if the error variance is higher for certain subjects compared to others, it is possible to calculate the independent error variance to evaluate the averages for subjects other than those with higher error variance. A disadvantage of the design is that the experimental error value increases when there are significant differences in soil, slope, and productivity between plots in the same block. This situation is particularly noticeable when the number of plots is high.

2.2 Latin Square Design

The Latin square design plan is preferred in cases where the test material exhibits heterogeneity in both the horizontal and vertical directions [9]. In this design, the number of rows, columns, and treatments must be equal; ideally, the number of treatments should be between 5 and 12. In 4×4 or smaller Latin squares, it is not recommended to use this design because the degree of error freedom will be low [10]. Care must be taken to arrange the plots in a square-like manner. In this design, each treatment appears only once in each row and column, so the effects of rows, columns, and treatments are independent of each other, and there is no interaction effect. Therefore, statistical analyses are simpler to perform, but analysis becomes difficult if a row or column is completely missing [11] .

From a standard Latin Square, many different Latin Squares can be created by changing the positions of rows and columns. For example, 576 different arrangements can be obtained from a 4×4 Latin Square. One of these arrangements should be randomly selected for distribution; however, this process can often be challenging in practice. In standard Latin squares, the first row and column typically contain the same values. When the number of treatments is insufficient, the Latin square can be repeated to increase the degree of error freedom.

If an observation is missing for any reason other than treatment effects, the value to be substituted is calculated using the following formula in the Latin square experimental design.

$$\hat{X} = \frac{k(R+C+M) - 2G}{(k-1)(k-2)} \quad (3)$$

In the above formula, k = number of transactions, R = sum of other observations in the row where the missing observation is located, C = sum of other observations in the column where the missing observation is located, M = sum of other elements of the transaction to which the missing observation belongs, and G = sum of all other recorded observations except for the missing observation.

In the case of two missing observations, the average of the averages of the row, column, and transactions to which one of the missing observations belongs is first assigned as a temporary value in place of that observation. The value of the other missing observation is calculated using the above equation. The estimated value found is assigned to the relevant observation, and then a new value is calculated according to the equation by subtracting the temporary value. This process is repeated until the values for both observations are fixed.

2.2.1 Strengths and Weaknesses of the Latin Square Design

In this design, the requirement to repeat the experiment as many times as the number of subjects is considered the main limitation. This design is particularly recommended for experiments with more than eight subjects. The most commonly used Latin squares are between 5×5 and 8×8. It can also be applied to designs smaller than 5×5; however, effective statistical analyses cannot be performed in these designs due to the low degree of freedom associated with experimental error. For example, there is no degree of freedom associated with experimental error in a 2×2 design, while this value is 2 in a 3×3 design and only 6 in a 4×4 design. Generally, when the degrees of freedom for error are below 10, a reliable F-test cannot be performed. However, in cases where, when smaller designs like 2×2 or 3×3 must be used arranging two Latin squares side by side is proposed as an alternative solution.

2.3 Nested or Hierarchial Designs

In certain multifactorial experiments, the levels of one factor (e.g., factor B) may be similar to each other; however, the levels of another factor (e.g., factor A) may differ. Such arrangements are referred to as nested or hierarchical designs [12] [13]. In these designs, the levels of factor B are nested within the levels of factor A.

For example, consider a company that sources its raw materials from three different locations. The company wants the purity of the raw materials to be the same across all three sources. Let each supplier's raw material be divided into four clusters of links, and let three different purity measurements be taken from each link. Such a situation is illustrated in Figure 1 [14].

This is a two-stage nested or hierarchical design with clusters grouped under each supplier. If these factors are crossed, the representatives of the first, second, and third links should be considered in that order. However, since each connection belongs to a specific seller, the situation is unclear. For example, there is no relationship between the first connection of seller 1 and the first connection of seller 2. This applies to all other connections of the sellers as well.

To emphasize that the ties of the sellers are different from each other, when the ties of seller number 1 are renumbered as 1, 2, 3, 4; the ties of seller number 2 as 5, 6, 7, 8; and the ties of seller number 3 as 9, 10, 11, 12, Figure 1 is obtained.

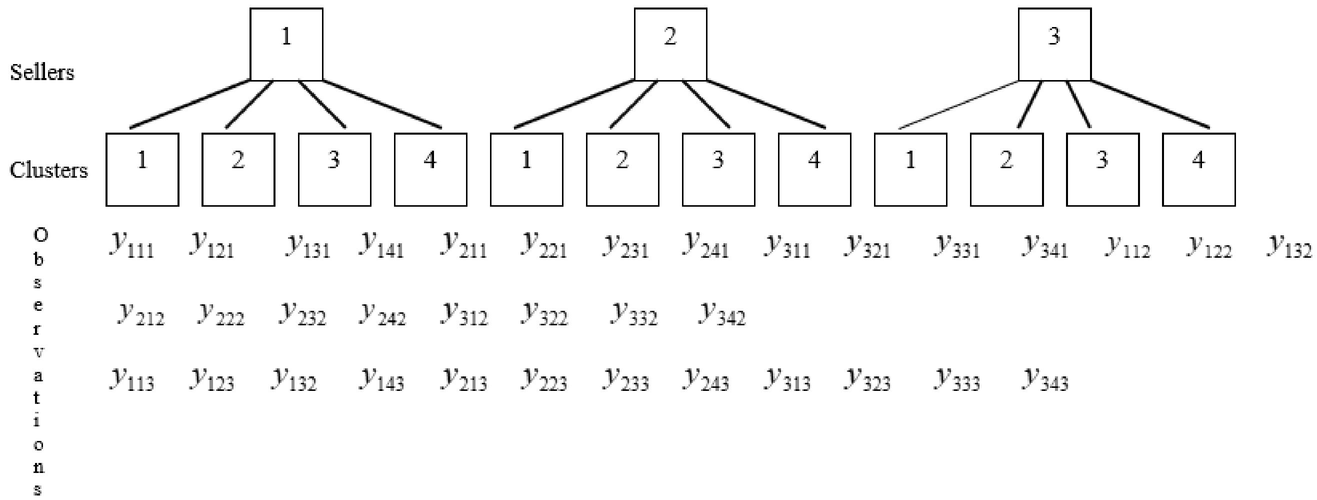

Figure 1: Two-Stage Nested Design

Sometimes it is not possible to make a definitive judgment as to whether a factor has been interchanged or nested. If the experiments for the factor in question are randomized and renumbered as shown in Figure 1, that factor is evaluated with its nested structure.

2.4 Split Plot Design

Split-plot design is used in two-factor experiments [15]. One of these factors is expected to have more experimental units than the other [16]. In alloy production, an experiment can be planned to compare the effects of different levels of temperature with casting molds. In this experiment, when the materials obtained from each furnace are divided into different types of casting molds, it is assumed that there are 3 levels of the furnace (A) and 4 levels of the casting mold (B). The randomized split-plot design is shown in Figure 2 below with 3 replicates. Each replicate consists of 3 large units, where each large unit represents the type of furnace, and each large unit is divided into 4 plots, with each plot representing the type of casting mold.

	Repeat-1		Repeat-2		Repeat-3
a_1	$b_1\ b_3\ b_4\ b_2$	a_3	$b_3\ b_4\ b_2\ b_1$	a_1	$b_2\ b_4\ b_1\ b_3$
a_2	$b_2\ b_4\ b_1\ b_3$	a_1	$b_1\ b_3\ b_4\ b_2$	a_2	$b_4\ b_1\ b_3\ b_2$
a_3	$b_4\ b_1\ b_3\ b_2$	a_2	$b_2\ b_1\ b_3\ b_4$	a_3	$b_3\ b_2\ b_4\ b_1$

Figure 2: Split Plot Design

In field trials, this design causes additional factors to emerge in the experiment due to the division of each block into multiple plots. In this design, it is assumed that factor A is tested at three levels. Dividing each unit into four parts for factor A requires factor B to be expanded to four levels. Within each unit of factor A, the 4 levels of factor B are created in 4 random parcels. The situation after randomization is observed in a manner similar to the above plan. In split-plot designs, the largest units are called main plots, and the smallest units are called subplots. The concept of randomness is addressed in two stages. It occurs in the allocation of main plot experiments to the main plot and the division of subplot experiments into subplots within each main plot. In the classical split-plot design, the main plots are arranged in randomly placed blocks. In main plot designs, alternative designs such as Incomplete Randomized Blocks or Latin Squares can also be used. The following explanations are based on the assumption that the main plots have a random design [17]. The appropriate mathematical model for this design is provided below.

$$y_{ijk} = \mu + \rho_i + \alpha_j + \delta_{ij} + \beta_k + (\alpha\beta)_{jk} + \varepsilon_{ijk} \quad (4)$$

In the above formula, $i = 1,2,...,r$, $j = 1,2,...,a$, $k = 1,2,...,b$, μ: are taken as mass average, ρ_i: as block/repeat effect, α_j: as main plot trial effect, δ_{ij}: as error rate of main plot effects, β_k: as sub-plot trial effect, $(\alpha\beta)_{jk}$: as main plot trial*sub-plot trial interaction effect, ε_{ijk}: as random sub-plot error.

In a 4×3 factorial experiment, Randomized Block Design can be used instead of Split-Plot Design, and both approaches have their own advantages. Randomized Block Design controls all main effects and interactions equally, while Split-Plot Design generally controls B and A×B interactions more effectively. In Split-Plot Design, the degrees of freedom for the error term used to compare the main plot factor (A) are lower. When evaluated overall, the mean error variance for both designs is similar; therefore, Split-Plot Design does not provide a significant advantage in terms of overall precision. However, the Split-Plot Design provides higher sensitivity in B and A×B effects; this advantage is achieved at the expense of ignoring some details in the A factor.

The greatest advantage of the Split-Plot Design is that it allows topics requiring large plots to be studied together with topics that can be conducted in small plots in the same experiment [18]. Thus, additional factors can be included in the experiment at a lower cost by using smaller plots. However, one of the weaknesses of this design is that its statistical analysis is more complex due to its reliance on two different error terms. This complexity increases, especially in cases of missing data. Additionally, testing the main plot factor with an error term that has a lower degree of freedom can lead to some imbalances. For example, small differences at the subplot level may be statistically significant, while larger differences at the main plot level may not be significant.

3. Overview of Multidisciplinary Applications in Experimental Design

Experimental designs are an indispensable part of research processes in many disciplines, ranging from engineering to social sciences, health to agriculture. Through a multidisciplinary approach, this study will examine how methods are adapted to various fields, which statistical techniques are preferred, and the effects of design strategies on research quality, all under separate subheadings. This will enable an investigation into the universal validity and adaptability of experimental design.

3.1 Science and Engineering

Experimental designs are widely used in science and engineering to improve product quality, reduce process variability, and optimize resource utilization. In particular, the Randomized Block Design (RCBD) stands out as a powerful tool for reducing systematic errors. Karthikeyan and colleagues investigated an optimization method for bending copper plates using RCBD to systematically evaluate the effects of various experimental conditions [19]. The integration of block designs in an engineering context exemplifies the adaptability of RCBD beyond traditional research areas and facilitates sophisticated evaluations in materials engineering.

Tian and colleagues used a method they called PFMECA in diesel engine production [20]. The researchers discussed the reliability assessment of the method in question. Another study examining the effectiveness of RCBD was conducted by Kasianova and colleagues [21] [20]. The researchers investigated the capacity of experimental designs to enhance power in multi-armed trials that adapt to response dynamics. The impact of the experimental learning skills developed by Fardillah and colleagues on industrial engineering students was observed, and it was shown that they are important in developing statistical reasoning skills [22]. They revealed that statistical designs in engineering have an important educational dimension.
In conclusion, experimental designs are widely preferred in

science and engineering to improve product quality, reduce process variability, and optimize resource utilization. In particular, the Randomized Block Design (RCBD) stands out as a powerful tool for reducing systematic errors. It is accepted as a fundamental design strategy in experimental research methodologies.

3.2 Health and Clinical Sciences

When examining studies in the field of health and clinical research in recent years, it has been observed that statistical experimental designs are used to support effective decision-making processes. Statistical experimental design can support researchers in interpreting scientific results aimed at understanding health outcomes in many studies. One of the fundamental principles of the statistical experimental design approach is to prioritize results with high scientific significance rather than focusing solely on simple statistical thresholds such as p-values. Reynolds emphasizes that experiments should be structured in line with answerable scientific questions and that problems should be addressed with in-depth experimental designs [23]. Karahan and Karaağaoğlu highlight the importance of receiving appropriate biostatistical support from the outset of the research process in their study [24]. The researchers note that experimental designs have the potential to increase the reliability of data produced in treatment methods, particularly drugs and vaccines.

Levin and Kratochwill define single-case intervention experimental designs as a valuable method for evaluating intervention effects at the individual level [25]. These designs can be used particularly in the fields of psychological and behavioral health. These experimental designs, which include single-case interventions, can reveal details that traditional large-sample designs cannot capture by taking individual differences into account. This allows for better results regarding patient responses that cannot be generalized from collective data.

Another method that is increasingly preferred in the evaluation of health services is the interrupted time series experimental design. Ewusie and colleagues draw attention to the existence of many interacting factors in health service environments [26]. Researchers state that the interrupted time series experimental design can analyze this complexity in healthcare settings and that statistical science provides a powerful methodological framework. In addition, the response surface methodology experimental design (RSM) offers a valuable approach to optimizing conditions in health research. Ho and colleagues note that the response surface methodology experimental design is an effective method for evaluating interactions among multiple variables and optimizing responses, particularly in comparative studies aimed at process improvement [27]. Researchers have highlighted that this approach is extremely useful for developing new treatment methods or making existing protocols more efficient.

In conclusion, the application of statistical experimental design in health and clinical research is critical for improving research quality, producing valid and reliable findings, and developing more effective solutions to complex health problems. The integration of experimental designs plays an important guiding role in research aimed at interpreting health data.

3.3 Agricultural and Food Sciences

Current studies in the field of agricultural and food sciences reveal that statistical experimental design applications are becoming increasingly important in the optimization of agricultural and food science systems. Experimental design, one of the prominent methods in agricultural experiments, enables the effective use of multivariate analyses. Amiri and colleagues noted in their study that experimental design was effective in determining the relationships between various agricultural parameters such as fertilization and plant density, and that it increased the accuracy of yield predictions [28]. The researchers emphasized how advanced statistical methods can benefit farmers, researchers, and policymakers in solving critical problems.

Kim and colleagues, in their research on weed management, used balanced experimental designs, took into account the variability in agricultural data, and thereby increased the statistical power and validity of their hypothesis tests [29]. Statistical experimental designs also play an important role in applications aimed at the efficient use of agricultural inputs. Rodriguez and colleagues demonstrated how they optimized soil restoration through statistical models developed from experimental data in their study on the remediation of hydrocarbon-contaminated soils [30]. The study conducted by the researchers showed that statistical experimental designs can make important contributions not only to yield increases but also to environmental sustainability.

In another recent study, Alesso and colleagues conducted research on the technical, ergonomic, and economic constraints encountered in on-farm research [31]. The researchers developed methods to enhance the reliability of experiments using spatial statistical approaches. These studies demonstrate that statistical experimental design, when combined with technology-focused applications, offers more innovative and applicable solutions in agricultural sciences. Freitas and colleagues, on the other hand, conducted a study on low-carbon agricultural practices in Brazil [32]. The researchers demonstrated in their study that traditional experimental designs can effectively address today's agricultural problems by using single and multivariate analysis methods. The findings of the study support the applicability of sustainable land use and effective monitoring systems.

In conclusion, statistical experimental design applications in agricultural and food sciences have been observed to guide the integration of technological developments into the field of agricultural and food sciences and increase productivity. Statistical experimental design approaches ensure scientific accuracy and pave the way for sustainable agricultural practices.

3.4 Social and Educational Sciences

Recent studies in the fields of social sciences and education reveal a growing interest in the application of statistical experimental designs with the aim of improving educational outcomes, better understanding human behavior, and evaluating different pedagogical approaches. Englis and Frederiks examine experimental design research methods in the fields of natural sciences, social sciences, and entrepreneurship education from a historical perspective [33]. The researchers emphasize the need for rigorous methodologies to effectively evaluate educational interventions. They also suggest that experimental designs can contribute to a deeper understanding of entrepreneurship ecosystems and pedagogical processes. In a similar study, Schanz and Giles analyzed the service-learning model using an experimental design [34]. The researchers demonstrated that the service-learning application had positive effects on student attitudes and learning outcomes.

Sukirman and colleagues used a single case study design within a quantitative research approach to evaluate the effectiveness of blended learning methods [35]. The researchers' findings reveal that experimental designs are an effective tool for measuring changes in educational performance before and after the implementation of new teaching strategies. Kükürtçü and Erkan used a quasi-experimental pretest-posttest design in their study on children's rights education [36]. The researchers evaluated changes in children's democratic behaviors and demonstrated the multifaceted potential of experimental designs in the social sciences.

In another study conducted specifically on the education of gifted students, Yurtbakan and Batmaz used a pre-post test design without a control group to evaluate the effectiveness of the support education program [37]. Their findings emphasize the role of empirical methods in improving the educational experiences of gifted individuals and demonstrate the applicability of such experimental research designs in different educational contexts. In parallel with technological developments in educational practices, Li focuses on the development of interactive educational tools that integrate data science methods with traditional social science education [38]. This approach provides an example of how statistical frameworks can be applied in innovative ways to increase student participation in the learning process.

In conclusion, the current literature demonstrates that statistical experimental approaches, including quasi-experimental designs and randomized controlled trials, provide robust methodological frameworks for evaluating educational practices in the social sciences. This empirical orientation is of critical importance for both policy development processes and the improvement of pedagogical approaches. Future research is encouraged to explore innovative designs, such as citizen social science, that could make the empirical research process more participatory.

4. Conclusion

This study examines both the theoretical foundations of experimental design and its diversity in practice. The extent to which statistical approaches are decisive in the process from planning to analyzing experiments has been demonstrated in concrete terms with examples from different disciplines. Classic designs such as randomized blocks and Latin squares remain effective methods for reducing heterogeneity in the field and controlling error variance. Split plots and nested designs, on the other hand, enable balance to be achieved in more complex arrangements. However, issues such as missing data problems and the proper management of error terms highlight the importance of statistical knowledge in this field.

In interdisciplinary studies, the applicability of experimental designs varies, but they are not merely theoretical tools; they have broad applicability in many fields such as science, engineering, health, social sciences, and agricultural sciences. The appropriate use of experimental designs in the above-mentioned fields will contribute significantly to making accurate and effective decisions and developing processes that maximize benefits. Considering the prediction that integrated experimental approaches with technologies such as artificial intelligence and big data will gain more importance in the future, the success of an experimental study in any scientific field depends on the selection of the correct design and support with appropriate statistical analysis. In this context, it is of great importance for researchers to possess not only statistical techniques but also interdisciplinary thinking skills.

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