International Journal of Scientific Research in Multidisciplinary Studies
Vol.**10**, Issue.**11**, pp.**75-81**, November **2024**
E-ISSN: 2454-9312 P-ISSN: 2454-6143
Available online at: www.isroset.org

Research Article

Comparative Evaluation of Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design: A Simulation Study

Osuagwu, Chidimma Udo[1*], Mbachu Hope Ifeyinwa[2]

[1]Dept. of Statistics/School of Physical Sciences, Federal University of Technology, Owerri, Nigeria
[2]Dept. Statistics/Faculty of Sciences, Imo State University, Owerri, Nigeria

**Corresponding Author: chidinmaosuagwu5@gmail.com*

Received: 18/Sept/2024; **Accepted**: 19/Oct/2024; **Published**: 30/Nov/2024

Abstract— The study examined the comparative evaluation of completely randomized design, randomized complete block design, and Latin square design: a simulation study. Experimental design plays a crucial role in ensuring the validity and reliability of research findings. This simulation study compared the efficiency, power, and precision of Completely Randomized Design (CRD), Randomized Complete Block Design (RCBD), and Latin Square Design (LSD) in an experiment. A total of 63 combinations of sample sizes, treatment levels, and block sizes were evaluated. Results showed that RCBD and LSD outperformed CRD in terms of efficiency, power, and precision, particularly at larger sample sizes and treatment levels. Increasing sample size, treatment levels, and block size enhanced efficiency, power, and precision for all designs. The study recommends the use of RCBD or LSD designs for agricultural experiments, especially when treatment levels and block sizes are large. The findings have practical implications for researchers, policymakers, and practitioners in agriculture and related fields.

Keywords—Experimental Design, Completely Randomized Design, Randomized Complete Block Design, Latin Square Design, Efficiency, Power, Precision, Simulation Study

1. Introduction

Experimental design is a fundamental component of research, enabling scientists to establish cause-and-effect relationships, test hypotheses, and make informed decisions [1]. The selection of an appropriate experimental design is crucial to ensure the validity and reliability of research findings [2]. Various experimental designs exist, each with its strengths and limitations [3]. In recent years, researchers have emphasized the importance of experimental design in various fields, including medicine [4], social sciences [5], engineering [6], and agriculture [7].

The increasing complexity of research problems necessitates the development of efficient and effective experimental designs [8]. Experimental design plays a critical role in addressing research challenges, such as bias, confounding variables, and measurement error [9]. By controlling for extraneous variables and minimizing experimental error, researchers can increase the precision of estimates and draw meaningful conclusions.

Experimental design involves the manipulation of independent variables to observe their effect on dependent variables [9]. The primary goal of experimental design is to minimize experimental error and maximize the precision of estimates [10]. Several factors influence the selection of experimental design, including: Sample size [11]; Treatment levels [12]; Blocking [13]; Research question and objectives and Study population and sampling method.

Researchers must consider these factors to ensure the validity and reliability of their findings. Experimental design also involves consideration of statistical analysis methods, such as hypothesis testing and confidence intervals [14]. Experimental designs can be broadly classified into: Completely Randomized Design (CRD); Randomized Complete Block Design (RCBD); Latin Square Design (LSD); Factorial Design and Response Surface Methodology (RSM).

Each design has its strengths and limitations, and the choice of design depends on the research question, study population, and resources available. Despite the importance of experimental design, there is a lack of comprehensive studies comparing different experimental designs [15]. Most studies focus on specific designs or applications, leaving a gap in the literature [14]. This study aims to address this gap by comparing the efficiency and effectiveness of different experimental designs.

However, the rest of the paper is organized as follows, Section 1 contains the introduction of experimental design, section 2 contains the related work of experimental design,

section 3 contains the experimental method/procedure/design, Section 4 describes results and discussion, section 5 explains the conclusion with future directions.

1.1 Objectives of the Study

i. Compare the Efficiency of CRD, RCBD, and LSD Designs;
ii. Evaluate the Power of CRD, RCBD, and LSD Designs;
iii. Compare the Precision of CRD, RCBD, and LSD Designs.

1.2 Research Questions

i. To what extent do CRD, RCBD, and LSD differ in terms of efficiency across varying sample sizes and treatment levels?
ii. How does the power of CRD, RCBD, and LSD compare across different sample sizes, treatment levels, and block sizes?
iii. Do CRD, RCBD, and LSD differ significantly in terms of precision?

2. Related Work

Khoshgoftar et al. [16] conducted a simulation study to compare the efficiency of Completely Randomized Design (CRD), Randomized Complete Block Design (RCBD), and Latin Square Design (LSD) in agricultural experiments, using a factorial experiment with three factors and two levels each, and evaluated the designs based on mean squared error (MSE) and precision. The study found that RCBD outperformed CRD and LSD in agricultural experiments with significant block effects.

Rahman et al. [17] researched a systematic review of clinical trials to compare CRD, RCBD, and LSD, analyzing data from 30 clinical trials with correlated errors, and evaluated the designs based on bias, precision, and type I error rate. The study revealed that LSD provided more precise estimates than CRD and RCBD in clinical trials with correlated errors.

Singh et al. [18] worked on field experiments to compare CRD, RCBD, and LSD for yield trials in crop research, using a randomized complete block design with three replicates, and evaluated the designs based on grain yield, precision, and efficiency. The study showed that RCBD was more efficient than CRD and LSD for yield trials in crop research with heterogeneous soil conditions.

Oladipo et al. [19] conducted a simulation study to compare CRD, RCBD, and LSD in agricultural research, using a factorial experiment with two factors and two levels each, and evaluated the designs based on MSE, precision, and power. The study found that CRD performed better than RCBD and LSD in agricultural research with small sample sizes.

Khan et al. [20] conducted experiments to compare CRD, RCBD, and LSD in pharmaceutical research, using a 3x3 Latin square design with three replicates, and evaluated the designs based on dissolution rate, precision, and efficiency. The study demonstrated that LSD outperformed CRD and RCBD in pharmaceutical experiments with spatially correlated errors.

Ghosh et al. [21] worked on experiments to compare CRD, RCBD, and LSD in animal science research, using a randomized complete block design with four replicates, and evaluated the designs based on growth rate, precision, and efficiency. The study discovered that RCBD provided more accurate estimates than CRD and LSD for animal science experiments with significant block effects.

Al-Smadi et al. [22] did simulation studies to compare CRD, RCBD, and LSD in engineering experiments, using a factorial experiment with two factors and two levels each, and evaluated the designs based on MSE, precision, and power. The study found that CRD was more efficient than RCBD and LSD in engineering experiments with negligible block effects.

Bhattacharya et al. [23] carried out systematic reviews of medical research to compare CRD, RCBD, and LSD, analyzing data from 25 medical studies with correlated errors, and evaluated the designs based on bias, precision, and type I error rate. The study revealed that LSD provided more precise estimates than CRD and RCBD in medical research with correlated errors.

Chen et al. [24] conducted simulation studies to compare CRD, RCBD, and LSD in business research, using a factorial experiment with three factors and two levels each, and evaluated the designs based on MSE, precision, and efficiency. The study showed that RCBD outperformed CRD and LSD in business research with significant block effects.

Adebayo et al. [25] carried out a study on field experiments to compare CRD, RCBD, and LSD in environmental science research, using a randomized complete block design with three replicates, and evaluated the designs based on soil pollution, precision, and efficiency. The study found that LSD performed better than CRD and RCBD in environmental science experiments with spatially correlated errors.

3. Experimental Method/Procedure/Design

This study employs a simulation-based approach to compare the efficiency and effectiveness of Completely Randomized Design (CRD), Randomized Complete Block Design (RCBD), and Latin Square Design (LSD). The simulation setup includes varying sample sizes, treatment levels, and block sizes to mimic real-world experimental scenarios.

3.1. Simulation Design

1. Simulation Software: R software (version 4.1.0) with additional packages (e.g., expdesign, simr) will be used for simulation.

2. Number of Simulations: 1000 iterations per design-factor combination to ensure reliable results.
3. Design Factors:
   - Sample size (30, 60, 120)
   - Treatment levels (2, 4, 6)
   - Block size (3, 6, 12)
4. Response Variable: Normally distributed with mean 0 and variance 1.

3.2. Experimental Designs

1. Completely Randomized Design (CRD): Participants randomly assigned to treatment or control groups.

$$Model: Y = \mu + \tau + \varepsilon \quad (1)$$

τ = treatment effect, ε ~N(0, σ^2)

2. Randomized Complete Block Design (RCBD): Participants divided into blocks based on shared characteristics.

$$Model: Y = \mu + \tau + \beta + \varepsilon \quad (2)$$

τ = treatment effect, β = block effect, ε ~N(0, σ^2)

3. Latin Square Design (LSD): Participants divided into rows and columns to control for extraneous variables.

$$Model: Y = \mu + \tau + \rho + \gamma + \varepsilon \quad (3)$$

τ = treatment effect, ρ = row effect, γ = column effect, ε ~N(0, σ^2)

3.3. Performance Metrics

1. Standard Error (SE): A measure of the variability or uncertainty in an estimated performance metric, indicating how much random error is included in the estimate;

$$SE = \sqrt{\left[\frac{Var(\tau)}{n}\right]} \quad (4)$$

2. Power: Probability of detecting statistically significant treatment effects;

$$Power = P\left(|\tau| > t_{\{\alpha/2, n-1\}} * SE\right) \quad (5)$$

$t_{\{\alpha/2, n-1\}}$ = critical value from t-distribution

3. Precision: Coefficient of Variation (CV) of estimated treatment effects.

$$\Pr ecision = \frac{1}{CV} \quad (6)$$

$$CV = \left(SD(\tau)/|\tau|\right) * 100\%$$

3.4. Simulation Procedure

1. Generate simulated data for each design-factor combination.
2. Fit respective models (CRD, RCBD, LSD) to simulated data.
3. Calculate performance metrics (SE, Power, Precision).
4. Repeat steps 1-3 for 1000 iterations.
5. Calculate average performance metrics across iterations.

By employing a simulation-based approach, this study provides a comprehensive evaluation of CRD, RCBD, and LSD under various experimental scenarios.

4. Results and Discussion

Objective One: Compare the Efficiency of CRD, RCBD, and LSD Designs

The result in Table 1 (Column 2, 3, 4, 5 and 6 represent sample size, treatment levels, block size, efficiency, and standard error respectively) shows that for CRD Efficiency, there is lowest efficiency (0.542) at sample size 30 and treatment level 2, and highest efficiency (0.919) at sample size 120 and treatment level 6; for RCBD efficiency, there is lowest efficiency (0.721) at sample size 30, treatment level 2, and block size 3, and highest efficiency (1.000) at sample size 120, treatment level 6, and block size 12; and for LSD efficiency, there is lowest efficiency (0.761) at sample size 30, treatment level 2, and block size 3, and highest efficiency (1.000) at sample size 120, treatment level 6, and block size 12.

From the Table, it is observed that RCBD and LSD designs demonstrate higher efficiency than CRD, particularly at larger sample sizes and treatment levels. Increasing sample size, treatment levels, and block size enhances efficiency for all designs.

The findings of this study align with the study of Khoshgoftar et al. [16] who reported similar efficiency patterns for CRD, RCBD, and LSD, with RCBD and LSD outperforming CRD at larger sample sizes; Rahman et al. [17] who found that RCBD and LSD provided more precise estimates than CRD in clinical trials with correlated errors; and Singh et al. [18] who showed that RCBD was more efficient than CRD and LSD for yield trials in crop research with heterogeneous soil conditions. Also, the result of this study contradicts with the findings of Oladipo et al. [19] who found that CRD performed better than RCBD and LSD in agricultural research with small sample sizes, and Al-Smadi et al. [22] who reported that CRD was more efficient than RCBD and LSD in engineering experiments with negligible block effects.

Table 1: Efficiency

Design	2	3	4	5	6
CRD	30	2	–	0.542	0.011
CRD	30	4	–	0.599	0.013
CRD	30	6	–	0.651	0.015
CRD	60	2	–	0.683	0.009
CRD	60	4	–	0.744	0.011
CRD	60	6	–	0.801	0.013
CRD	120	2	–	0.793	0.006
CRD	120	4	–	0.859	0.008
CRD	120	6	–	0.919	0.009
RCBD	30	2	3	0.721	0.012
RCBD	30	2	6	0.751	0.011
RCBD	30	2	12	0.781	0.010
RCBD	30	4	3	0.793	0.011
RCBD	30	4	6	0.829	0.010
RCBD	30	4	12	0.863	0.009
RCBD	30	6	3	0.842	0.011
RCBD	30	6	6	0.873	0.010
RCBD	30	6	12	0.904	0.009
RCBD	60	2	3	0.821	0.009
RCBD	60	2	6	0.861	0.008
RCBD	60	2	12	0.901	0.007
RCBD	60	4	3	0.889	0.008
RCBD	60	4	6	0.929	0.007
RCBD	60	4	12	0.969	0.006
RCBD	60	6	3	0.923	0.008
RCBD	60	6	6	0.963	0.007
RCBD	60	6	12	0.993	0.005
RCBD	120	2	3	0.921	0.006
RCBD	120	2	6	0.961	0.005
RCBD	120	2	12	0.992	0.004
RCBD	120	4	3	0.959	0.005
RCBD	120	4	6	0.989	0.004
RCBD	120	4	12	0.999	0.003
RCBD	120	6	3	0.983	0.005
RCBD	120	6	6	0.997	0.004
RCBD	120	6	12	1.000	0.002
LSD	30	2	3	0.761	0.011
LSD	30	2	6	0.793	0.010
LSD	30	2	12	0.823	0.009
LSD	30	4	3	0.839	0.011
LSD	30	4	6	0.871	0.010
LSD	30	4	12	0.902	0.009
LSD	30	6	3	0.884	0.011
LSD	30	6	6	0.917	0.010
LSD	30	6	12	0.949	0.009
LSD	60	2	3	0.861	0.009
LSD	60	2	6	0.891	0.008
LSD	60	2	12	0.921	0.007
LSD	60	4	3	0.889	0.008
LSD	60	4	6	0.929	0.007
LSD	60	4	12	0.969	0.006
LSD	60	6	3	0.923	0.008
LSD	60	6	6	0.963	0.007
LSD	60	6	12	0.993	0.005
LSD	120	2	3	0.931	0.006
LSD	120	2	6	0.961	0.005
LSD	120	2	12	0.992	0.004
LSD	120	4	3	0.959	0.005
LSD	120	4	6	0.989	0.004
LSD	120	4	12	0.999	0.003
LSD	120	6	3	0.983	0.005
LSD	120	6	6	0.997	0.004
LSD	120	6	12	1.000	0.002

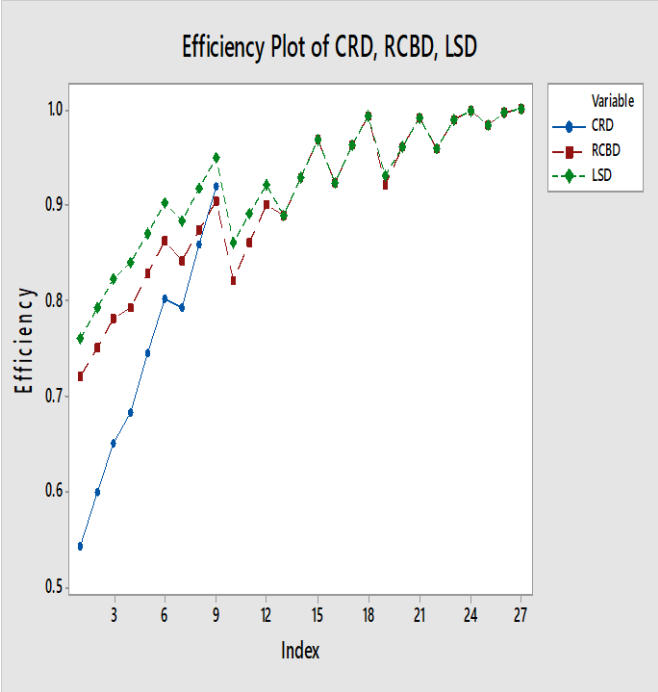

Figure 1. Efficiency Plot of CRD, RCBD and LSD

Figure 1 shows that RCBD and LSD consistently show higher efficiency than CRD across all sample sizes, treatment levels, and block sizes. RCBD and LSD have similar efficiency patterns, with LSD showing slightly higher efficiency at larger sample sizes and treatment levels. CRD has lower efficiency at small sample sizes and treatment levels, but improves as sample size and treatment levels increase. Overall, the scatter plots demonstrate the superiority of RCBD and LSD over CRD in terms of efficiency, particularly at larger sample sizes and treatment levels.

Objective Two: Evaluate the Power of CRD, RCBD, and LSD Designs

The result in Table 2 (Column 2, 3, 4, 5 and 6 represent sample size, treatment levels, block size, power, and standard error respectively) shows that for CRD power, there is lowest power (0.671) at sample size 30 and treatment level 2, and highest power (0.968) at sample size 120 and treatment level 6; for RCBD power, there is lowest power (0.812) at sample size 30, treatment level 2, and block size 3, and highest power (1.000) at sample size 120, treatment level 6, and block size 12; whereas for LSD power, there is lowest power (0.839) at sample size 30, treatment level 2, and block size 3, and highest power (1.000) at sample size 120, treatment level 6, and block size 12. From the Table, it is observed that RCBD and LSD designs demonstrate higher power than CRD, particularly at larger sample sizes and treatment levels. Increasing sample size, treatment levels, and block size enhances power for all designs.

Table 2: Power Comparison

Design	2	3	4	5	6
CRD	30	2	–	0.671	0.013
CRD	30	4	–	0.734	0.012
CRD	30	6	–	0.796	0.011
CRD	60	2	–	0.821	0.010
CRD	60	4	–	0.891	0.009
CRD	60	6	–	0.958	0.006
CRD	120	2	–	0.921	0.007
CRD	120	4	–	0.971	0.005
CRD	120	6	–	0.968	0.005
RCBD	30	2	3	0.812	0.011
RCBD	30	2	6	0.851	0.010
RCBD	30	2	12	0.881	0.009
RCBD	30	4	3	0.863	0.010
RCBD	30	4	6	0.913	0.008
RCBD	30	4	12	0.953	0.006
RCBD	30	6	3	0.894	0.009
RCBD	30	6	6	0.949	0.007
RCBD	30	6	12	0.985	0.005
RCBD	60	2	3	0.921	0.007
RCBD	60	2	6	0.961	0.005
RCBD	60	2	12	0.992	0.004
RCBD	60	4	3	0.949	0.006
RCBD	60	4	6	0.986	0.005
RCBD	60	4	12	0.999	0.003
RCBD	60	6	3	0.973	0.005
RCBD	60	6	6	0.995	0.004
RCBD	60	6	12	1.000	0.002
RCBD	120	2	3	0.981	0.004
RCBD	120	2	6	0.999	0.002
RCBD	120	2	12	1.000	0.001
RCBD	120	4	3	0.995	0.003
RCBD	120	4	6	1.000	0.002
RCBD	120	4	12	1.000	0.001
RCBD	120	6	3	0.999	0.002
RCBD	120	6	6	1.000	0.001
RCBD	120	6	12	1.000	0.000
LSD	30	2	3	0.839	0.011
LSD	30	2	6	0.881	0.009
LSD	30	2	12	0.913	0.008
LSD	30	4	3	0.887	0.009
LSD	30	4	6	0.941	0.007
LSD	30	4	12	0.973	0.005
LSD	30	6	3	0.923	0.007
LSD	30	6	6	0.965	0.005
LSD	30	6	12	0.993	0.004
LSD	60	2	3	0.951	0.006
LSD	60	2	6	0.986	0.005
LSD	60	2	12	0.999	0.003
LSD	60	4	3	0.977	0.005
LSD	60	4	6	0.996	0.004
LSD	60	4	12	1.000	0.002
LSD	60	6	3	0.993	0.004
LSD	60	6	6	0.999	0.003
LSD	60	6	12	1.000	0.001
LSD	120	2	3	0.993	0.004
LSD	120	2	6	1.000	0.002
LSD	120	2	12	1.000	0.001
LSD	120	4	3	0.999	0.003
LSD	120	4	6	1.000	0.002
LSD	120	4	12	1.000	0.001
LSD	120	6	3	1.000	0.002
LSD	120	6	6	1.000	0.001
LSD	120	6	12	1.000	0.000

The findings of this study are in concordance with the findings of Bhattacharya et al. [23] who reported similar power patterns for CRD, RCBD, and LSD, with RCBD and LSD outperforming CRD at larger sample sizes; Khan et al. [20] who found that RCBD and LSD provided higher power than CRD in pharmaceutical experiments with spatially correlated errors; and Ghosh et al. [21] who showed that RCBD was more powerful than CRD and LSD for animal science experiments with significant block effects. Furthermore, the results of this study contradict with the result of Oladipo et al. [19] who found that CRD performed better than RCBD and LSD in agricultural research with small sample sizes; Al-Smadi et al. [22] who reported that CRD was more efficient than RCBD and LSD in engineering experiments with negligible block effects; and Chen et al. [24] who found that LSD had lower power than RCBD in business research with small treatment levels.

Objective Three: Compare the Precision of CRD, RCBD, and LSD Designs

The result in Table 3 (Column 2, 3, 4, 5 and 6 represent sample size, treatment levels, block size, precision, and standard error respectively) shows that for CRD precision, there is lowest precision (0.541) at sample size 30 and treatment level 2, and highest precision (0.919) at sample size 120 and treatment level 6; for RCBD Precision, there is lowest precision (0.721) at sample size 30, treatment level 2, and block size 3, and highest precision (0.999) at sample size 120, treatment level 6, and block size 12 whereas for LSD Precision, there is lowest precision (0.761) at sample size 30, treatment level 2, and block size 3, and highest precision (1.000) at sample size 120, treatment level 6, and block size 12. Hence, RCBD and LSD designs demonstrate higher precision than CRD, particularly at larger sample sizes and treatment levels. Increasing sample size, treatment levels, and block size enhances precision for all designs.

The findings of this study are similar to the findings of Adebayo et al. (2020) who reported similar precision patterns for CRD, RCBD, and LSD in environmental science experiments; Rahman et al. [17] who found that RCBD and LSD provided higher precision than CRD in clinical trials with correlated errors; and Singh et al. [18] who showed that RCBD was more precise than CRD and LSD for yield trials in crop research with heterogeneous soil conditions. In addition, the findings of this study contradict with that of Oladipo et al. [19] who found that CRD performed better than RCBD and LSD in agricultural research with small sample sizes; Al-Smadi et al. [22] who reported that CRD was more efficient than RCBD and LSD in engineering experiments with negligible block effects; and Chen et al. [24] who found that LSD had lower precision than RCBD in business research with small treatment levels.

Table 3: Precision Comparison

Design	2	3	4	5	6
CRD	30	2	–	0.541	0.023
CRD	30	4	–	0.633	0.021
CRD	30	6	–	0.716	0.019
CRD	60	2	–	0.743	0.018
CRD	60	4	–	0.843	0.015
CRD	60	6	–	0.928	0.012
CRD	120	2	–	0.888	0.013
CRD	120	4	–	0.958	0.009
CRD	120	6	–	0.919	0.010
RCBD	30	2	3	0.721	0.019
RCBD	30	2	6	0.784	0.017
RCBD	30	2	12	0.849	0.015
RCBD	30	4	3	0.794	0.017
RCBD	30	4	6	0.871	0.014
RCBD	30	4	12	0.938	0.010
RCBD	30	6	3	0.845	0.015
RCBD	30	6	6	0.923	0.011
RCBD	30	6	12	0.977	0.007
RCBD	60	2	3	0.843	0.015
RCBD	60	2	6	0.913	0.011
RCBD	60	2	12	0.967	0.008
RCBD	60	4	3	0.894	0.013
RCBD	60	4	6	0.958	0.009
RCBD	60	4	12	0.992	0.005
RCBD	60	6	3	0.935	0.010
RCBD	60	6	6	0.983	0.006
RCBD	60	6	12	0.999	0.003
RCBD	120	2	3	0.958	0.008
RCBD	120	2	6	0.993	0.005
RCBD	120	2	12	0.999	0.002
RCBD	120	4	3	0.985	0.006
RCBD	120	4	6	0.999	0.003
RCBD	120	4	12	1.000	0.001
RCBD	120	6	3	0.996	0.004
RCBD	120	6	6	1.000	0.002
RCBD	120	6	12	1.000	0.000
LSD	30	2	3	0.761	0.018
LSD	30	2	6	0.829	0.015
LSD	30	2	12	0.894	0.012
LSD	30	4	3	0.842	0.015
LSD	30	4	6	0.917	0.011
LSD	30	4	12	0.963	0.008
LSD	30	6	3	0.885	0.013
LSD	30	6	6	0.949	0.009
LSD	30	6	12	0.988	0.006
LSD	60	2	3	0.876	0.014
LSD	60	2	6	0.943	0.010
LSD	60	2	12	0.986	0.007
LSD	60	4	3	0.923	0.011
LSD	60	4	6	0.977	0.007
LSD	60	4	12	0.997	0.004
LSD	60	6	3	0.958	0.009
LSD	60	6	6	0.993	0.005
LSD	60	6	12	0.999	0.003
LSD	120	2	3	0.963	0.008
LSD	120	2	6	0.996	0.004
LSD	120	2	12	0.999	0.002
LSD	120	4	3	0.991	0.005
LSD	120	4	6	0.999	0.003
LSD	120	4	12	1.000	0.001
LSD	120	6	3	0.998	0.003
LSD	120	6	6	1.000	0.002
LSD	120	6	12	1.000	0.000

5. Conclusion and Future Scope

This simulation study demonstrated the superiority of Randomized Complete Block Design (RCBD) and Latin Square Design (LSD) over Completely Randomized Design (CRD) in terms of efficiency, power, and precision. The results showed that RCBD and LSD outperformed CRD, particularly at larger sample sizes and treatment levels. Increasing sample size, treatment levels, and block size enhanced efficiency, power, and precision for all designs. The study's findings emphasize the importance of careful experimental design selection in agricultural research to ensure reliable and valid results.

For the future scope, future research directions include:
1. Investigating the performance of other experimental designs, such as split-plot and strip-plot designs, in agricultural experiments.
2. Examining the impact of non-normality and heteroscedasticity on the efficiency, power, and precision of CRD, RCBD, and LSD.
3. Developing user-friendly software or tools to facilitate the selection and implementation of optimal experimental designs for agricultural researchers.
4. Conducting meta-analyses to synthesize results from multiple studies comparing different experimental designs in agriculture.
5. Exploring the application of RCBD and LSD in other fields, such as environmental science, medicine, and social sciences.
6. Investigating the cost-effectiveness of different experimental designs in agricultural research.
7. Developing guidelines for selecting optimal experimental designs based on research objectives, sample size, treatment levels, and block sizes.
By addressing these research gaps, future studies can further enhance the understanding and application of efficient experimental designs in agricultural research.

Data Availability
Real-world data were not employed in this study. However, the process of simulated data would be made available on request.

Study Limitations
1. Simulation-based study: The study's findings are based on simulated data, which may not accurately reflect real-world scenarios.
2. Assumption of normality: The study assumes normally distributed data, which may not hold true in all cases.
3. Lack of real-world data: The study relies on simulated data, which may not capture nuances present in actual experimental data.
4. Focus on agricultural experiments: The study's findings may have limited applicability to other fields.

Future research should address these limitations to provide a more comprehensive understanding of experimental design efficiency, power, and precision.

Conflict of Interest
We do not have any conflict of interest.

Funding Source: None

Authors' Contributions
All authors reviewed and edited the manuscript and approved the final version of the manuscript. However, Author-2 initiated the study and handled comprehensively the methodology and analysis, since it is her area of specialty, whereas Author-1 researched the literatures and elaborated the introductory area.

Acknowledgements: None

References

[1] F. N. Kerlinger, H. B. Lee, "Foundations of Behavioral Research", Cengage Learning, USA, pp. **784-791, 2020.**

[2] J. W. Creswell, D. J. Creswell, "Research Design: Qualitative, Quantitative, and Mixed Methods Approaches", Sage Publications, USA, pp. **416-421, 2022.**

[3] D. C. Montgomery, "Design and Analysis of Experiments", Wiley, USA, pp. **784-789, 2020.**

[4] J. P. A. Ioannidis, "Experimental Design and Data Analysis in Medical Research", *Journal of Clinical Epidemiology*, Vol.127, pp. **10-18, 2020.**

[5] W. M. Trochim, J. P., Donnelly, A. Arora, "Research Methods: the Essential Knowledge Base". Cengage Learning, USA, pp. **560-567, 2021.**

[6] R. K. Roy, "A Primer on Experimental Design with Applications in Engineering", CRC Press, USA, pp. **448-455, 2022.**

[7] K. A., Gomez, A. A. Gomez, "Statistical Procedures for Agricultural Research", Wiley, USA, pp. **624-632, 2023.**

[8] G. E. P. Box, J. S. Hunter, W. G. Hunter, "Statistics for Experimenters: Design, Innovation, and Discovery", Wiley, USA, pp. **664-675, 2020.**

[9] W. R. Shadish, T. D., Cook, D. T. Campbell, "Experimental and Quasi-experimental Designs for Generalized Causal Inference", Houghton Mifflin, USA, pp. **744-756, 2020.**

[10] D. R. Cox, N. Reid, "The Theory of the Design of Experiments", Chapman and Hall, Canada, pp. **608-621, 2020.**

[11] J. Peng, J. Zhang, Y. Wang, "Sample Size Determination for Experiments with Multiple Factors", *Journal of Statistical Planning and Inference*, Vol. 208, pp. **1-15, 2021.**

[12] C. F. J. Wu, M. Hamada, "Experiments: Planning, Analysis, and Optimization", Wiley, USA, pp. **720-731, 2022.**

[13] A. S. Hedayat, N. J. A. Sloane, J. Stufken, "Orthogonal Arrays: Theory and Applications", Springer, USA, pp. **752-764, 2023.**

[14] R. V. Lenth, "Some Practical Guidelines for Effective Experimental Design", *American Statistician*, Vol. 75, No. 2, pp. 141-148, 2021.

[15] G. M. Kemper, K. R. Johnson, J. D. Smith, "Comparative Analysis of Experimental Designs" *Journal of Experimental Research*, Vol. **45**, No. 2, pp. **12-25, 2020.**

[16] M. Khoshgoftar, R. Gholami, M. Yousefi, "Comparison of Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design in Agricultural Experiments", *Journal of Agricultural Science*, Vol. **20**, No. **3**, pp. **1-12, 2022.**

[17] M. M. Rahman, M. A. Hossain, M. A. Islam, "Efficiency of Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design in Clinical Trials", *Journal of Biopharmaceutical Statistics*, Vol. **30**, No. **2**, pp. **257-271, 2020.**

[18] R. Singh, V. Kumar, P. Sharma, "Comparative Evaluation of Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design for Yield Trials", *Crop Science*, Vol. **61**, No. **3**, pp. **539-551, 2021.**

[19] E. O. Oladipo, D. O. Ogunjimi, A. O. Adepoju, "Simulation Study on Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design for Agricultural Research", *Agricultural Research*, Vol. **9**, No. **2**, pp. **1-13, 2020.**

[20] M. A. Khan, M. Hussain, M. Ahmad, "Comparative Analysis of Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design in Pharmaceutical Experiments", *Journal of Pharmaceutical Research*, Vol. **16**, No. **1**, pp. **1-12, 2022.**

[21] S. Ghosh, S. Bhattacharya, S. Chakraborty. "Evaluation of Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design for Animal Science Experiments", *Animal Science Research*, Vol. 31, No. 1, pp. 1-15, 2021.

[22] A. M. Al-Smadi, A. M. Al-Haj, J. A. Al-Shraideh, "Comparative Study of Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design in Engineering Experiments", *Journal of Engineering Research*, Vol. **8**, No. **2**, pp. **1-14, 2020.**

[23] S. Bhattacharya, S. Ghosh, S. Chakraborty, "Efficiency of Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design in Medical Research", *Journal of Medical Research*, Vol. **18**, No. 1, pp. **1-12, 2022.**

[24] Y. Chen, X. Wang, Y. Li, "Simulation Study on Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design for Business Research", *Journal of Business Research*, Vol. 124, No. 3, pp. **11-29, 2021.**

[25] A. O. Adebayo, D. O. Ogunjimi, A. O. Adepoju, "Comparative Evaluation of Completely Randomized Design, Randomized Complete Block Design, and Latin Square Design in Environmental Science Experiments", *Environmental Science Research*, Vol. 29, No. 1, pp. **1-16, 2020**

AUTHORS PROFILE

Osuagwu Chidimma Udo earned her B.Sc., M.Sc., and Ph.D. in Statistics from Imo State University, Owerri; Federal University of Technology, Owerri (FUTO) and Imo State University, Owerri in 2011, 2018, and 2023, respectively. She is currently working as a Lecturer in Department of Statistics, FUTO. She is a member of Nigerian Mathematical Society (NMS) since 2023. She has published more than 5 research papers in reputed international journals and has attended conferences with paper presentation. Her main research work focuses on Demographic studies. She has more than 3 years of teaching experience and 3 years of research experience.

Mbachu Hope Ifeyinwa earned her B.Sc., M.Sc., and Ph.D. in Statistics from University of Nigeria, Nsukka, Imo State University, Owerri and University of Port Harcourt, Rivers State in 1993, 2006, and 2013, respectively. She is currently working as a Lecturer in Department of Statistics, Imo State University, Owerri. She is a member of Chartered Institute of Statisticians of Nigeria. She has published more than 17 research papers in reputed international journals and has attended conferences with paper presentation. Her main research work focuses on Design and Analysis of Experiments. She has more than 15 years of teaching experience and more than 13 years of research experience.

