CONTINUOUS MEDICAL EDUCATION

Sample Size Estimation in Clinical Trials

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DOI: 10.55489/njcm.150620243815

A B S T R A C T

Sample size estimation remains as a cornerstone in the meticulous planning and execution of clinical trials, pivotal for ensuring studies possess the requisite statistical power to discern meaningful treatment effects. Insufficient sample sizes compromise the robustness of findings, whereas excessively large samples inflate costs and compromise data integrity. This article meticulously explains the multifaceted factors that outline sample size determination, encompassing various factors such as research design, types of hypotheses, error thresholds, effect size considerations, validity and precision. It investigates into the scope of methodologies available for sample size computation, spanning from intricate statistical formulas to pragmatic tabular approaches. Moreover, it underscores the significance of post-hoc power analysis in retrospectively evaluating completed studies, shedding light on their statistical robustness. This literature review furnishes a nuanced understanding of the sample size estimation landscape in clinical trials, delineating their strengths, limitations, and real-world applications. Anticipating participant attrition assumes paramount importance for pro-actively adjusting sample sizes, ensuring studies remain methodologically sound. Equipped with a profound grasp of these principles, researchers are empowered to conduct scientifically rigorous and impactful clinical trials, furnishing compelling evidence to inform judicious decision-making in healthcare interventions.

Key Words: Sample size, Statistically significant, Clinically significant, Type I error, Type II error, Power

ARTICLE INFO

Financial Support: None declared Conflict of Interest: None declared Received: 14-02-2024, Accepted: 24-04-2024, Published: 01-06-2024 Correspondence: Dr Divyangkumar Patel (Email: drdivpatel@gmail.com)

How to cite this article: Patel DN. Sample Size Estimation in Clinical Trials. Natl J Community Med 2024;15(6):503-508. DOI: 10.55489/njcm.150620243815

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INTRODUCTION

Conducting medical research demands substantial resources, including manpower, time, and materials. A significant challenge arises when, upon completing a study, investigators realize that the research lacks the necessary statistical power to accurately estimate the significance of results, thereby compromising the study's ability to reliably estimate the observed outcomes.^{1,2}

Inadequate sample size raises concerns about the validity of observed findings. Both insufficient and excessively large sample sizes, compared to the required size, present challenges. A small sample size is associated with missed effects and imprecise estimates, while a large sample size leads to increased costs and compromised data quality. Consequently, determining the optimal sample size for each study is essential.^{1,2}

Randomized Controlled Trials (RCTs) are widely regarded as the gold standard for evaluating healthcare interventions. Unlike observational studies, randomization in RCTs is a powerful method for balancing confounding factors between treatment groups, effectively eliminating the impact of potential variables that could skew results. When designing a clinical trial, determining the optimal sample size is a crucial consideration to ensure significant results.¹

In the study by Pierre Charles et al., it was found that 5% of RCTs did not provide any information regarding sample size calculations, and 43% failed to report all the necessary parameters require for calculating sample size. Furthermore, in 30% of the RCTs, there was a deviation exceeding 10% between the reported sample size in the article and the replicated sample size calculation. The reporting of sample size calculations remains inadequate, often containing errors and relying on assumptions that are frequently inaccurate.³

The main goal of determining sample size is to ascertain a suitable number of participants for a specific study design, ensuring a balance between obtaining meaningful results and optimizing resource utilization.

Sample size challenges in a study are addressed in two stages: during the planning phase, researchers calculate the optimal size using relevant methods, and in situations with constraints like finances or rare diseases, post-hoc power analysis is conducted after completing the study with available sample.

This article aims to elucidate the factors that impact sample size estimation in clinical trials and provide guidance for appropriate sample size calculation.

Key Factors Influencing Sample Size Determination

Sample size calculation depends on various factors

such as research design, primary outcome measure, hypothesis (one or two-tailed), precision, type I error, type II error, power, effect size, design effect, etc. To grasp the principles of sample size calculation and power analysis, it is essential to comprehend these commonly used terms.

2.1 Null hypothesis and alternate hypothesis⁴: The null and alternative hypotheses are two mutually exclusive statements about a population. The null hypothesis states that no difference exists among treatments or interventions, null hypothesis require to test. Conversely, the alternative hypothesis contradicts the null hypothesis, postulating a difference among treatments or interventions. If the alternative hypothesis cannot be directly tested, it is accepted, if the test of significance rejects the null hypothesis.

Two types of alternative hypotheses exist: the onetailed hypothesis, specifying a difference in one direction only, and the two-tailed hypothesis, specifying a difference in either direction. For instance, a one-tailed hypothesis might suggest that Drug A is more effective compared to Drug B for the treatment of Diabetes, while a two-tailed hypothesis proposes a difference in effectiveness among Drug A and Drug B in diabetes treatment, either higher or lower effectiveness.

The choice between one- or two-tailed approaches depends on the clinical or biological significance of the research question and prior knowledge about the effect or association. This decision should not be driven by sample size considerations only, as it hinges on the contextual importance of the research question. Value of Z_{α} is lower for one sided hypothesis compared to two-sided hypothesis so sample size lower for one side hypothesis compared to two side hypotheses.

2.2 Type I (α) error, Type II (β) error and Statistical Power (1- β): In a study involving a sample population, discrepancies between the derived results and reality are termed as "errors". When study carried out among sample population there may be four possibilities exist in identifying differences between two treatments: (1) correctly concluding no difference among two treatments, (2) incorrectly concluding a difference among treatments when none exists, (3) incorrectly concluding no difference among treatment when difference present and (4) correctly concluding a difference among treatments.

Sometimes in reality null hypothesis is true mean treatments are not different but we conclude that treatments are different means we reject the null hypothesis and accept the alternative hypothesis; this the error in experiment and it called as Type I error or α error. The probability of making α error is called as level of significance (P value). Generally, it is considered as 0.05 (5%). What does P < 0.05 mean? It means the probability of α error is less than 0.05 (or 1 in 20).

| Hypothesis testing outcome | | REALITY | | | | | |
|----------------------------|--|---|---|--|--|--|--|
| | | Treatments are not difference The null hypothesis (H0) is true | Treatments are different The Alternative hypothesis (H1) is true | | | | |
| ARCH | Conclude treatments are not different The null hypothesis (H0) is true | Correct decision (Cell a) | Type II error β error (Cell b) | | | | |
| RESE/ | Conclude treatments are different The Alternative hypothesis (H0) is true | Type I error α error (Cell c) | Correct decision Power (1-β) (Cell d) | | | | |

Table 1: Possible outcomes of a randomized trial: type I, type II errors and power

If you see the right half of Table- 1, there may be two types of possibilities of result. When in reality treatments are different, one possibility is result conclude that treatments are different (Cell d) and other possibility is result conclude that treatments are not different, this is an error, it is called as type II error or β error. It is the situation when in reality null hypothesis is rejected but results conclude that null hypothesis is true.

Power is the correctly identifying that treatments are different mean in reality alternative hypothesis is true and result also conclude that alternative hypothesis is true. It is denoted by $1-\beta$. In simple meaning, power of study is the number of participants require to avoid type II error.

Table 2 provides values for Z_{α} and Z_{β} for selected α and β . Sample size is inversely proportion to Type I and Type II error and directly proportional to Power (1- β).

Table 2: Unit normal deviates Z_{α} and Z_{β} for selected values of α or β

| αorβ | One sided Z_{α} and Z_{β} | Two sided Z_{α} |
|------|--|------------------------|
| 0.05 | 1.64 | 1.96 |
| 0.10 | 1.28 | 1.64 |
| 0.20 | 0.84 | 1.28 |
| | | 1 |

 $Z_{\boldsymbol{\beta}}$ is the same for one sided and two-sided tests

2.3 Error: Two types of errors can be introduced into a study: random error and systematic error. Random error is a result of chance, while systematic error is not solely due to chance. Systematic error is challenging to measure accurately. Random error can be minimized by employing strategies such as averaging, increasing sample size, and repeating the experiment to the acceptable level.

2.4 Effect Size: Effect size (ES) denotes the minimum difference that an investigator aims to detect between study groups, often referred to as the minimal clinically relevant difference. It signifies the magnitude of an effect in the alternative hypothesis, encapsulating the smallest difference that holds clinical or biological significance.^{5,6} Its relevance varies between studies; for instance, a 1% reduction in mortality may be significant, while a 20% reduction in transient asthma might not be clinically relevant. Increasing the effect size reduces type II error, and

power is contingent on both effect size and sample size. Larger sample sizes are needed for 'small effects' to achieve a given power compared to 'large effects'.⁵ The estimation of effect size can be accomplished through three methods: pilot studies, data from previous reports, or informed guesses derived from clinical experiences.⁶

2.5 Validity and Precision: Validity means the degree to which the variable actually measure what it is supposed to measure.⁸ It is a function of systematic error or bias. Precision, or reliability, indicates how consistently a variable maintains the same value across multiple measurements.² It is a measure of consistency and can be related to the width of the confidence interval. Precision is influenced by factors such as random error, sample size, confidence interval width, and variance of the outcome variable. A larger sample size contributes to more precise estimates^{2,8}.

2.6 Design effect: Cluster sampling is a cost-effective and practical approach compared to simple random sampling, simplifying studies by grouping units into clusters. When opting for cluster sampling instead of simple random sampling, it becomes necessary to adjust the sample size using a correction factor known as the "design effect." This design effect is the ratio of variance observed in a cluster survey to that in a simple random sample (SRS) of the same size.

The design effect can be determined from prior studies and is often expressed as a constant, typically ranging between 1 and 2. In practical applications, a design effect of 2 is commonly assumed. This assumption implies that, to achieve the same level of precision as with SRS, twice as many individuals would need to be included in the study when employing cluster sampling. Ideally, the design effect should be derived from previous data or pilot studies for more accurate estimation.

2.7 Type of clinical types¹: There are various clinical trial designs, with the parallel randomized controlled trial (RCT) being the most common. In this design, participants are randomly assigned to different interventions simultaneously, typically comparing a new treatment to a standard one.

• Superiority trials aim to establish that a new treatment is statistically or clinically more effective than a standard treatment. The null hypothe-

sis in this case states that the new treatment is not more efficacious than the control treatment.

- Equivalence trials seek to demonstrate that the new treatment and the standard treatment are equally effective. The null hypothesis for equivalence trials posits that the two treatments differ by a clinically relevant amount.
- Non-inferiority trials are conducted to show that the new treatment is as effective as, but not necessarily superior to, the standard treatment. The corresponding null hypothesis is that the new treatment is inferior to the control treatment by a clinically relevant amount.

Superiority and non-inferiority trials typically employ a one-sided test, while equivalence trials use a two-sided test. The sample size may be lower for ssuperiority and non-inferiority trials compared to equivalence trials. Selection of one sided or twosided hypothesis or test should not be based on the sample size consideration, it must be based on clinical significance. It is always better to use two sided hypothesis and test.⁹

Sample size estimation methods

The determination of sample size can be achieved through the using mathematical formulas, readymade reference tables, or specialized software packages. Essential information necessary for the calculation of sample size includes various parameters, which are the study design, anticipated effect size, desired statistical power, the requisite level of significance, and the design effect.

Statistical Formula:

The formula for calculating the sample size in a clinical trial varies based on the primary outcome, whether it is a mean or a proportion. The specific calculation formula is outlined below.

Example:

Sample size for comparative studies: means

To calculate the sample size, a previous study was taken in to account in which the Drug A was reduced a 50 mg/dl blood pressure after 3 weeks of treatment with SD 20 md/dl and Drug B was reduced a 40 mg/dl blood pressure after 3 weeks of treatment with SD of 10 mg/dl. If we desire an equal sample size in both groups, what would be the minimal sample size in each group to detect a difference with a power of 80% at 95% confidence level?

$$n = \frac{\left[\left(Z\alpha_{/2} + Z_{\beta} \right)^2 \times \{ 2(\sigma)^2 \} \right]}{(\mu_1 - \mu_2)^2}$$

Where,

n = sample size required in each group, $\mu 1$ = mean change in pain score from baseline to week 24 in Drug A = 50, $\mu 2$ = mean change in pain score from baseline to week 24 in Active drug = 40, $\mu 1-\mu 2$ = clinically significant difference = 10 δ = combined standard deviation = 16.549 $Z_{\alpha/2}$: This depends on level of significance, for 5% this is 1.96 Z_{β} : This depends on power, for 80% this is 0.84

n = $\frac{[(1.96+0.84)^2 X 2 (16.54)^2]}{(50-)^2} = \frac{7.84 X 547}{100} = 43$ in each group

Sample size for comparative studies: proportion

A placebo-controlled randomized trial proposes to assess the effectiveness of Drug A in curing children suffering from otitis media. A previous study showed that proportion of subjects cured by Drug A is 40% and a clinically important difference of 10% as compared to placebo is acceptable.

$$n = \frac{\left(Z\alpha_{/_2} + Z_{\beta}\right)^2 \quad [P_1(1 - P_1) + P_2(1 - P_2)]}{(P_1 - P_2)^2}$$

n = sample size required in each group,

p1 = proportion of subject cured by Drug A = 0.40,

p2 = proportion of subject cured by Placebo = 0.30,

p1-p2 = clinically significant difference = 0.10

 $Z_{\alpha/2}\!:$ This depends on level of significance, for 5% this is 1.96

 Z_β : This depends on power, for 80% this is 0.84

n =
$$\frac{(1.96 + 0.84)^2}{(0.10)^2} = 352$$
 in each group

Tabular method:

Readymade table are available to calculate the sample size required for each group.

This table is designed for studies where the main outcome is a proportion or binary outcome. It helps to calculate sample size based on the effectiveness of two interventions derived from previous studies or pilot studies. To determine the sample size, you only need the lower of the two cure rates and the difference in cure rates between the two treatment groups. The term "cure rate" can be substituted with "effectiveness" or the "desired outcome".

| Lower of the | | | | DIFFER | ENCES IN | CURE RA | TES BETW | EEN THE | TWO TRE | ATMENT (| GROUPS | | | |
|----------------|-------|------|------|--------|----------|---------|----------|---------|---------|----------|--------|------|------|------|
| Two Cure Rates | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | 0.30 | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 |
| 0.05 | 420 | 130 | 69 | 44 | 36 | 31 | 23 | 20 | 17 | 14 | 13 | 11 | 10 | 8 |
| 0.10 | 680 | 195 | 96 | 59 | 41 | 35 | 29 | 23 | 19 | 17 | 13 | 12 | 11 | 8 |
| 0.15 | 910 | 250 | 120 | 71 | 48 | 39 | 31 | 25 | 20 | 17 | 15 | 12 | 11 | 9 |
| 0.20 | 1,090 | 290 | 135 | 80 | 53 | 42 | 33 | 26 | 22 | 18 | 16 | 12 | 11 | 9 |
| 0.25 | 1,250 | 330 | 150 | 88 | 57 | 44 | 35 | 28 | 22 | 18 | 16 | 12 | 11 | _ |
| 0.30 | 1,380 | 360 | 160 | 93 | 60 | 44 | 36 | 29 | 22 | 18 | 15 | 12 | _ | _ |
| 0.35 | 1,470 | 370 | 170 | 96 | 61 | 44 | 36 | 28 | 22 | 17 | 13 | — | — | — |
| 0.40 | 1,530 | 390 | 175 | 97 | 61 | 44 | 35 | 26 | 20 | 17 | _ | _ | _ | - |
| 0.45 | 1,560 | 390 | 175 | 96 | 60 | 42 | 33 | 25 | 19 | — | — | - | — | _ |
| 0.50 | 1,560 | 390 | 170 | 93 | 57 | 40 | 31 | 23 | _ | _ | _ | _ | _ | _ |

Source: Gordis Epidemiology - Six edition

Figure 1: Sample size needed in clinical trial (α=0.05) and Power=0.80 (Two-sided test)

| Lower of the | | | | DIFFER | ENCES IN | CURE RA | TES BETW | EEN THE | TWO TRE | ATMENT (| GROUPS | | | |
|----------------|-------|------|------|--------|----------|---------|----------|---------|---------|----------|--------|----------|------|------|
| Two Cure Rates | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | 0.30 | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 |
| 0.05 | 330 | 105 | 55 | 40 | 33 | 24 | 20 | 17 | 13 | 12 | 10 | 9 | 9 | 8 |
| 0.10 | 540 | 155 | 76 | 47 | 37 | 30 | 23 | 19 | 16 | 13 | 11 | 11 | 9 | 8 |
| 0.15 | 710 | 200 | 94 | 56 | 43 | 32 | 26 | 22 | 17 | 15 | 11 | 10 | 9 | 8 |
| 0.20 | 860 | 230 | 110 | 63 | 42 | 36 | 27 | 23 | 17 | 15 | 12 | 10 | 9 | 8 |
| 0.25 | 980 | 260 | 120 | 69 | 45 | 37 | 31 | 23 | 17 | 15 | 12 | 10 | 9 | |
| 0.30 | 1,080 | 280 | 130 | 73 | 47 | 37 | 31 | 23 | 17 | 15 | 11 | 10 | _ | - |
| 0.35 | 1,160 | 300 | 135 | 75 | 48 | 37 | 31 | 23 | 17 | 15 | 11 | - | _ | _ |
| 0.40 | 1,210 | 310 | 135 | 76 | 48 | 37 | 30 | 23 | 17 | 13 | — | - | _ | |
| 0.45 | 1,230 | 310 | 135 | 75 | 47 | 36 | 26 | 22 | 16 | - | - | <u> </u> | | |
| 0.50 | 1,230 | 310 | 135 | 73 | 45 | 36 | 26 | 19 | — | — | | | _ | |

Source: Gordis Epidemiology – Six edition

Figure 2: Sample size needed in clinical trial (α =0.05) and Power=0.80 (one sided test)

Post hoc power analysis

Researchers have the option to calculate power after completing a study using various software packages. An example of a straightforward and open-source tool is OpenEpi, which can be accessed through www.openepi.com. By navigating to the menu bar, users can open the power analysis section and input parameters such as sample size for two groups, effect size, or proportion of effect in both groups.

Example: After conducting a study with a sample size of 352 in each group, we obtained the following effect. What is the statistical power of this study?

n = sample size in each group=352

p1 = proportion of subject cured by Drug A = 0.40

p2 = proportion of subject cured by Placebo = 0.30

| Power for Randon | nized Clinical | Trials |
|-------------------------------------|----------------------|---|
| | 95 | Í. |
| Confidence Interval (%) {two-sided} | | Enter between 0 and 100, usually 95% |
| | Treatment Group 1 | Treatment Group 2 |
| Sample Size | 352 | 352 |
| Percent with outcome (%) | 40 | 30 |

Figure 3: Calculation of power of RCT

| 1 | nput Data |
|---|-----------|
| Two sided-confidence interval (%) | 95 |
| Sample size of Treatment Group 1 | 352 |
| Percent with outcome in Treatment Group 1 (%) | 40 |
| Sample size of Treatment Group 2 | 352 |
| Percent with outcome in Treatment Group 2 (%) | 30 |
| Risk ratio detected | 1.3 |
| Power based on: | |
| Normal approximation | 79.56% |
| Normal approximation with continuity correction | 77.2% |

Figure: 4 Result of calculation of power of RCT

The determined statistical power is 80%. We previously computed a sample size of 352, considering a similar effect size, with the aim of achieving 80% power and a 95% confidence interval.

In prospective studies, including clinical trials, the anticipated loss to follow-up or participant dropout (d) must be considered when determining the final sample size. The adjusted sample size (N1) to account for potential dropouts is calculated using the formula N1 = n / (1 - d). For instance, if the calculated sample size (n) is 350 and the dropout rate is 10%, the final adjusted sample size (N1) would be 350 / (1 - 0.10) = 389.7, rounded up to 390 participants.⁷ Dropout rate can be based on historical data from similar studies or pilot studies. A common rule of thumb is to assume a 10-20% dropout rate.

CONCLUSION

Sample size estimation is a crucial aspect of designing clinical trials, as it plays a pivotal role in ensuring the validity and reliability of study outcomes. The results obtained from such investigations serve as compelling evidence for making informed decisions regarding interventions.

Consequently, it is imperative for investigators to employ rigorous methods for calculating sample size. The utilization of various established approaches allows researchers to determine the optimal number of participants required for a study. A comprehensive understanding of the key factors influencing sample size calculations is essential for researchers to conduct scientifically sound and impactful clinical trials. By comprehensively reviewing the various sample size estimation methods, this research article aims to equip researchers, statisticians, and clinicians with a comprehensive understanding of the principles and practices involved in determining sample sizes for clinical trials.

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