# Applicability of the Bayesian Sample Size Determination in Tanzania's Demographic, Health, and Malaria Survey

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## Abstract

*This study illustrates an exciting case of sample sizes using the Bayesian method, which rests on Bayesian decision theory and the posterior criterion. A quantitative study design was used to demonstrate (SSD) using TDHM-MIS as secondary data, consisting of malaria prevalence among children under age five and a sample of children aged 6–59 months eligible for malaria testing. Analysis using (MCMC) simulation-based method, employed with the use of non-informative prior, the general-purpose fitting prior distribution and the informative prior as a subjective sampling prior that generates the data. The study showed that ALC has an optimal sample size, compared with ACC and WOC. Key findings suggest that the optimal sample sizes obtained were not similar, not only because of the choice of priors or lengths, but also because of the choice of SSD criteria that average over the predictive distribution of the unknown data. 95% confidence intervals favour ALC over ACC and WOC. Based on the findings, the study suggests using Bayesian techniques with highly informative priors because they reduce sample sizes to levels adequate to achieve a set of goals, as illustrated in the statistical simulation results.*

**Keywords:** *Bayesian techniques, Sample Size Determination (SSD), Average Length Criteria (ALC), Average Coverage Criteria (ACC), Worst Outcome Criteria (WOC).*

## 1.0 Introduction

Bayesian techniques have grown from classical statistics (frequentist alternative methods) to a mainstream statistical toolkit for empirical and applied research across epidemiology, spatial modelling, and clinical trial design (Kunzmann et al., 2020). Globally, advances in technology, computational techniques/tools, the increased availability of historical and primary data, and the development of decision-theoretic design criteria have made Bayesian approaches especially attractive for problems in which uncertainty must be formally incorporated into design and inference (Pan & Banerjee, 2023). Bayesian sample-size determination (SSD), using predictive (assurance) calculations, posterior-probability criteria, or formal decision-theoretic loss functions, has been the subject of substantial theoretical work and software development over the past decade. Recently, the literature shows that, in practice, fully Bayesian sample size determination is still primarily used in randomised clinical trials, with many studies relying on hybrid or frequentist-style justifications rather than transparent fully Bayesian techniques (Wilson, 2022).

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In parallel with global methodological advances, Bayesian methods have been increasingly applied to public health and epidemiological problems in Africa (Harrell, 2020). Currently, large-scale spatial and spatial-temporal studies using Bayesian geostatistical and hierarchical models have produced high-resolution maps and prevalence estimates for diseases such as tuberculosis and malaria across multiple countries, demonstrating the technique's ability to borrow strength across space and to quantify uncertainty at small geographic scales (Harrell, 2020). Bayesian methods, which leverage hierarchical priors, spatial random effects, and covariate information, produce estimates that are both statistically efficient and policy-relevant for resource allocation (Semakula, 2023).

At the country level, applications across Africa further illustrate the practical value of Bayesian modelling (Reis, 2024). Bayesian epidemiological and forecasting studies have been used to infer COVID-19 transmission dynamics and change-points in South Africa, and hierarchical Bayesian meta-analyses have been used to synthesise evidence on child health risk factors across sub-Saharan countries (Gharbharan et al., 2023). These applied works show how Bayesian approaches accommodate complex data structures (missing data, mining data, measurement error, temporally irregular observations) and produce probabilistic forecasts. Interval estimates that support decision making under uncertainty conditions (Kunzmann et al., 2021) and (Butler &Blackwell, 2023).

Recently, Tanzanian studies have applied Bayesian spatio-temporal models to malaria surveillance data, developed Bayesian state-space models and fuzzy-Bayesian inference for under-five mortality forecasting, and used Bayesian hierarchical approaches to explore cardiovascular disease trends and other population health outbreaks (Goligher et al., 2024). These works demonstrate not only the feasibility of Bayesian analyses using global, local and national data but also the value of explicitly quantifying uncertainty and spatial heterogeneity for national health planning. However, while Bayesian inference is being applied and gaining popularity in Tanzania for estimation and forecasting, there remains limited evidence of Bayesian sample size determination being used systematically in Tanzanian clinical and epidemiological study design; reporting on how sample sizes are chosen is often sparse or hybrid in nature (Goligher et al., 2024).

Taken together, the global methodological advances and the growing African and Tanzanian application literatures suggest both opportunity and need (Omair, 2024). Although Bayesian sample size determination methods (assurance, posterior criteria, and decision-theoretic calculations) offer principled ways to incorporate prior information and quantify the probability that a study meets its goals, recent systematic reviews highlight a gap between methodological recommendations and applied practice (Goligher et al., 2024).

According to Giovagnoli (2021), Bayesian methods have been proposed to integrate and explore the effects of uncertainty in the assumptions used to determine the optimal sample size when planning a study. For instance, methods such as assurance provide a toolkit for using expert opinion or historical data to give a more complete picture of the actual probability of success for a clinical trial and serve as a comprehensive complement to sensitivity analysis (Lan et al., 2022). Other methods, such as Mixed Bayesian likelihood, allow researchers to explore the cost of adopting Bayesian characteristics for the posterior probability while still using a frequentist method for estimation or testing (Pan & Turner,

2023). All these studies indicate that Bayesian methods can help formalise and increase the acknowledgement and consideration of the intrinsic uncertainty in sample size determination. However, there are no empirical studies that demonstrate the application of Bayesian techniques for optimal sample-size determination using Tanzania Demographic and Health Survey data.

This study aimed to illustrate a Bayesian approach to sample size determination for both non-informative and informative priors in estimating malaria prevalence, and to compare the resulting sample sizes using Bayesian sample size performance metrics. Markov Chain Monte Carlo (MCMC) is a simulation method used to infer distributions in Bayesian statistical modelling, given data and a prior distribution (Lam, 2020; Wong et al*., 2021)*. Secondary data from the Tanzania Demographic and Health Survey (TDHS) 2022 MIS were used to calculate sample sizes using performance metrics (ACL, ACC, and WOC). TDHS-MIS is a periodic survey conducted in Tanzania that serves as a source of population and health data for stakeholders, including demographers, health policymakers, programme managers, and research institutions.

## 2.0 Literature Review

### 2.1 Theoretical Review

This study is guided by four theories: Bayesian Sample Size determination theory, precision-based theory, posterior probability theory, and information-criteria theory**.**

#### 2.1.1 Bayesian Sample Size Determination Theory

Bayesian Sample Size determination theory provides a framework for deciding how many observations (sample) are needed in a study within the Bayesian paradigm. It is the body of principles and methods that define how to choose a sample size in Bayesian analysis. It is grounded in posterior inference, decision theory, predictive distributions, and information measures to ensure that the study yields sufficiently informative and decision-relevant results (O'Hagan & Stevens, 2001)**.**

#### 2.1.2 Precision-Based Criteria Theory

The theory illustrates that the required sample size is the minimum number of observations needed so that the posterior distribution of the parameters achieves a specified level of precision (usually measured by variance or credible interval width ). It describes how many observations are needed for the posterior to be sufficiently concentrated (precise) to make valid inferences (Joseph et al., 1997)**.**

#### 2.1.3 Posterior Probability Theory

Posterior Probability Theory, as articulated by Müller and Parmigiani (1996), posits that every unknown parameter (θ) is treated as a random variable with an associated probability distribution that is updated after observing data. The theory is grounded in Bayesian inference, in which prior beliefs about a parameter are combined with observed data using Bayes' theorem to generate a posterior distribution. This posterior distribution

reflects updated knowledge about the parameter, integrating both prior information and empirical evidence. Posterior probability theory is instrumental in statistical inference, providing a coherent framework for quantifying uncertainty and making decisions based on observed data.

### 2.1.4 Information Criteria Theory

Information Criteria Theory focuses on designing studies and selecting statistical models based on the amount of information they are expected to provide about unknown parameters. Rooted in Bayesian decision theory, this theoretical stream emphasises choosing models and sample sizes that yield sufficient information for reliable inference (Lindley, 1956; Bernardo, 1979). In this context, information criteria guide researchers in determining an appropriate sample size (n) that provides adequate information about the parameter (θ) while balancing model complexity and estimation precision. The theory supports efficient and objective decision-making in model selection and research design.

## 2.2 Empirical Review

Chen and Fraser (2022) used Monte Carlo simulations and demonstrated the applicability of the Bayesian approach to continuous, normally distributed data with a non-informative prior distribution. The prior distribution was flat, and a prior intervention did not contribute to the new study. However, the results could be easily extended to an informative prior distribution if reliable data are available. By using a non-informative prior distribution, researchers can design intervention studies and evaluate results within a Bayesian framework without searching for prior data that may be inappropriate or even misleading.

Khoo et al. (2023), in their systematic review of sample size determination in Bayesian randomised clinical trials, employed full Bayesian methods on 19,182 records, of which 8,870 were duplicates, and 10,312 were screened. 176 abstracts underwent full-text screening, and 105 studies were selected for data extraction. Findings demonstrate a slow increase in the number of RCTs using a Bayesian approach to analyse their primary efficiency data from 2012 onwards, with a sharp increase during the COVID-19 pandemic between 2020 and 2022 (50%). Results show that the most common method for sample size determination in Bayesian randomised clinical trials was a hybrid approach (61%), combining elements of Bayesian and frequentist theory. In comparison, 19% used a frequentist approach, 16% did not justify their approach, and only 4% used a truly Bayesian framework to calculate sample size (Mayo & Gajewski, 2024).

Sahu and Smith (2020) demonstrated the Bayesian method of sample size determination with practical applications. They explored some of the implications of a complete Bayesian framework for sample size determination. Their approach is general and can be used for many problems in statistical decision-making. They found that typical non-informative prior distributions lead to petite sample sizes. In contrast, a very informative prior distribution also leads to a minimal sample size when the prior mean is 'far' from the hypothesised value of the parameters, as revealed by (Fornacon, 2022). The sample sizes are largest when the prior distribution is highly concentrated at the hypothesised value of the parameter (Lee et al., 2021) and (Goligher, 2024). They felt that the Bayesian framework can incorporate practitioners' prior knowledge regarding the hypotheses and potential losses far more

naturally than the frequentist framework requires, and that auditors' views about the value of sampling (Pan, 2023).

Brus et al. (2022) studied a Bayesian approach to sample size determination, which was illustrated using soil health card data from Andhra Pradesh. In SSD, uncertainty about the parameter of interest, such as the population mean or the areal fraction, can be readily accounted for in a Bayesian approach. With the priors chosen in their study, the fully Bayesian and mixed Bayesian-likelihood sample sizes were comparable to the frequentist sample sizes, as measured by the average length (ALC) and average coverage (ACC) of the credible interval (Brus et al., 2022). When the worst-outcome criterion was used, these sample sizes were larger than the frequentist sample sizes, depending on the worst level (the proportion of most likely data sets). However, the fully Bayesian sample sizes for the population mean were conservative, assuming a prior sample size of 0 (Brus et al., 2022). With more realistic prior sample sizes, the fully Bayesian sample size became substantially smaller than the frequentist sample size (Grieve, 2022; Hopewell, 2025; Hermine, 2022). The fully Bayesian and mixed Bayesian-likelihood sample sizes are sensitive to the hyperparameters of the prior distributions (Golchi & Heath, 2024). Vasishth et al. (2023) demonstrated that sample sizes are robust to the choice of fitting priors, provided the priors are non-informative and sensitive to the parameter ranges. Furthermore, the study recommends specifying a likely range of values for a parameter and using a uniform distribution over this interval as its sampling prior for practical purposes.

Based on these studies, there is no solid body of theoretical and empirical literature regarding sample size determination (SSD) for Bayesian methods applied to Tanzania's demographic, health, and malaria survey. However, De Santis (2023) provides different approaches for determining sample size for testing the mean of a normal distribution with known variance. (Kruschke, 2023) and (Kruschke & Liddell, 2024) discuss parameter estimation and use the posterior distribution as a measure of the strength of evidence. Schönbrodt and Wagenmakers (2020) and Stefan et al. (2022) introduce Bayes factor design analysis applied to fixed-N and sequential designs.

This study illustrates a Bayesian method for determining the optimal sample size for Estimating Malaria prevalence in Tanzania, assuming a single imperfect test and ignoring the test's characteristics (sensitivity and specificity). Moreover, the study illustrated a practical comparison of sample sizes obtained with informative and non-informative priors for three Bayesian sample-size performance metrics (ALC, ACC, and WOC) using the Markov Chain Monte Carlo method.

## 3.0 Methodology

This study adopted a quantitative design to illustrate the Bayesian method, which enables researchers to analyse similarities and differences between informative and non-informative priors as well as performance metrics in Bayesian sample size determination. The primary focus was on demonstrating how optimal sample sizes are derived from the highest posterior density (HPD) of simulated sample distributions, computed via Markov

Chain Monte Carlo (MCMC). Secondary data from the Tanzania Demographic and Health Survey and the Malaria Indicator Survey (2022 TDHS-MIS) were used as input. Notably, the 2022 TDHS-MIS was the first DHS programme to include a malaria component; previously, the HIV/AIDS and Malaria Indicator Survey was conducted separately. Results showed that 14% of Tanzanian children aged 6–59 months tested positive for malaria using Rapid Diagnostic Tests (RDTs). Accordingly, this study applied Bayesian sample size determination to estimate malaria prevalence among children in this age group, using THS-MIS as prior information and TDHS-MIS as observed data.

The Bayesian framework combined analytical and simulation-based techniques via MCMC, given the absence of explicit sample-size formulas in Bayesian analysis. Two prior distributions were employed: a non-informative prior, serving as a general-purpose fitting prior, and an informative prior, representing expert subjective knowledge to generate parameter values and data. Simulated data supplemented method development by providing measurable characteristics that facilitated sample size determination (SSD).

The analysis involved specifying a probabilistic data model by identifying the response variable, selecting an appropriate probability distribution, and defining model parameters. Informative and non-informative priors were formulated to represent existing knowledge and uncertainty before observing new data. A likelihood function was constructed from the observed data, and posterior distributions were obtained by combining priors with the likelihood using Bayes' theorem. Computations were performed in R with MCMC methods to derive HPD intervals. Optimal sample sizes were determined using Bayesian performance criteria, namely the Average Length Criterion (ALC), Average Coverage Criterion (ACC), and Worst Outcome Criterion (WOC), to achieve a 95% posterior credible interval coverage. This approach enabled comparison of priors and facilitated estimation of optimal sample sizes.

## 4.0 Presentation and Discussion of the Findings

### 4.1 Presentation of Findings

This section introduces the application of Bayesian methods in sample size determination, highlighting their relevance in modern statistical analysis where traditional formulas are often inadequate. By integrating both informative and non-informative priors with observed data, Bayesian approaches provide a flexible framework for evaluating performance criteria and deriving optimal sample sizes. The study draws on secondary data from the Tanzania Demographic and Health Survey and the Malaria Indicator Survey (TDHS-MIS) to examine malaria prevalence among children aged 6–59 months. Using Markov Chain Monte Carlo (MCMC) simulations, the analysis demonstrates how Bayesian techniques can combine prior knowledge with empirical evidence to generate credible intervals and guide decision-making in health research.

**Table 4.1 Optimal Sample Sizes with their Corresponding Specified Lengths**

| Length $\left(\frac{L}{10}\right)$ | Different Priors $(\alpha, \beta)$ | Different Posteriors $(\overline{\alpha}, \overline{\beta})$ | Bayesian Sample Size (Performance metrics) | | |
|---|---|---|---|---|---|
| | | | ALC | ACC | WOC (95%) |
| 1. | Informative prior Beta (7,54) | Beta (13,107) | 15700 | 16000 | 38000 |
| | Non-Informative Prior Beta (1,1) | Beta (10,55) | 18600 | 19000 | 38400 |
| 2. | Informative prior Beta (7,54) | Beta (13,107) | 3900 | 3700 | 9500 |
| | Non-Informative Prior Beta (1,1) | Beta (10,55) | 4600 | 4760 | 9540 |
| 3. | Informative prior Beta (7,54) | Beta (13,107) | 1660 | 1700 | 4200 |
| | Non-Informative Prior Beta (1,1) | Beta (10,55) | 2010 | 2100 | 4300 |
| 4. | Informative prior Beta (7,54) | Beta (13,107) | 880 | 900 | 2300 |
| | Non-Informative Prior Beta (1,1) | Beta (10,55) | 1110 | 1100 | 2400 |
| 5. | Informative prior Beta (7,54) | Beta (13,107) | 520 | 530 | 1400 |
| | Non-Informative Prior Beta (1,1) | Beta (10,55) | 690 | 710 | 1480 |

**Source:** Field study, 2025

Average Length Criterion (ALC); Average Coverage Criterion (ACC); Worst Outcome (WOC) Criterion. Table 4.1 shows the optimal sample sizes obtained from three Bayesian Sample size criteria (WOC, ACC, ALC) when using an Informative prior for the Beta(7, 54) parameter and a non-informative Beta (1, 1) prior. WOC yields the largest sample size among ACC, ALC, and WOC, regardless of the specified length. The difference in optimal sample size across the criteria decreases as the specified length increases, with ACC and ALC approaching WOC. Also, the gap between WOC and other criteria is wider when the specified length is greater than for other specified lengths.

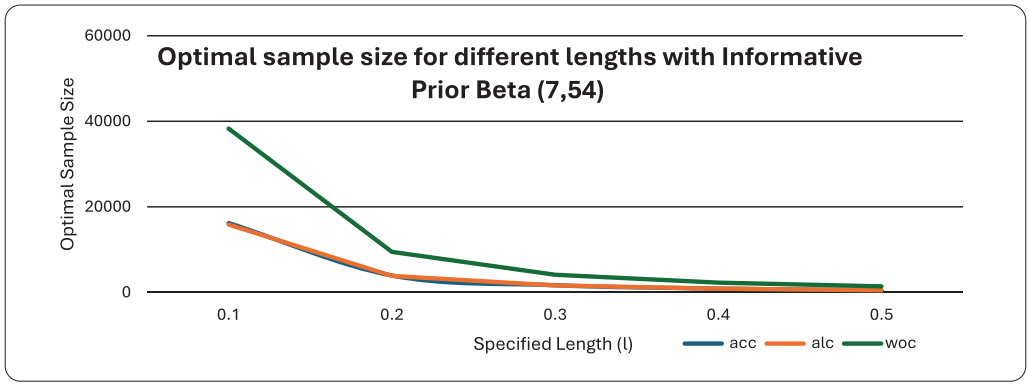


**Figure 4.1: Optimal sample size for different l with Informative Prior Beta (7, 54)**

**Source:** Field study, 2025

Figure 4.1 shows plots of optimal sample sizes obtained from three Bayesian sample size criteria (WOC, ACC, ALC) when using an informative prior for the Beta (7,54) parameter. WOC yields the largest sample size among ACC, ALC, and WOC, regardless of the specified length. The difference in optimal sample size across the criteria decreases as the specified

length increases, with ACC and ALC approaching WOC. Also, the gap between WOC and other criteria is wider when the specified length is greater than 3 than when it is less than 3.

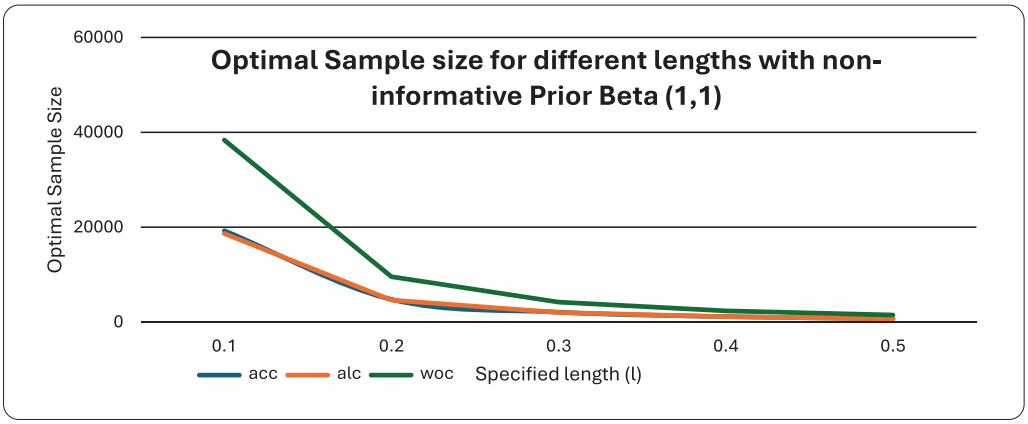


**Figure 4.2: Optimal Sample Size for Different *l* with Non-informative Prior Beta (1, 1)**
**Source:** Field study, 2025

Figure 4.2 shows a plot of optimal sample sizes obtained from three Bayesian Sample size criteria (WOC, ACC, ALC) when using a non-informative prior for the Beta (1,1) parameter. The WOC yields the maximum sample size among both ACC and ALC, regardless of the specified length. The gap between the optimal sample across the criteria decreases as the specified length increases, with ACC and ALC approaching WOC. Also, the gap between WOC and other criteria is wider when the specified length is greater than 3 than when it is less than 3.

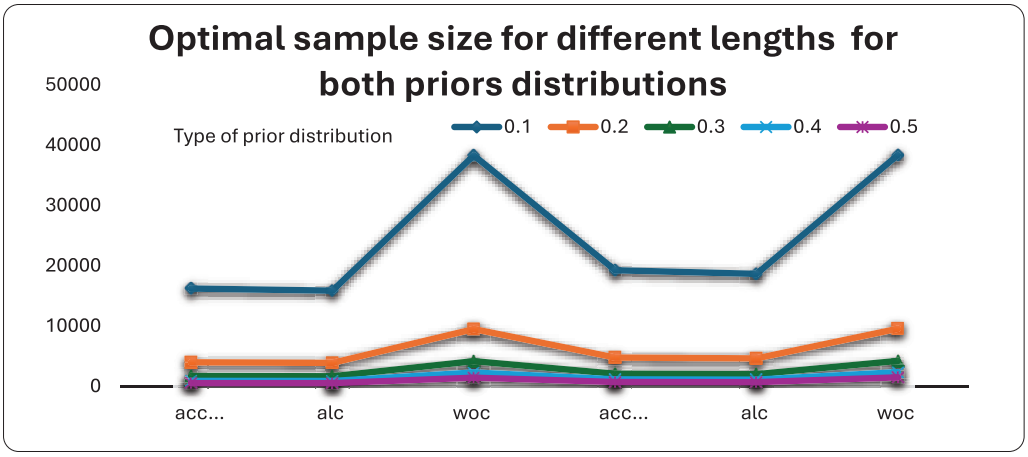


**Figure 4.3: Optimal Sample Size for Different Specified Lengths for both Priors' Distributions**
**Source:** Field study, 2025

Figure 4.3 shows a plot of optimal sample sizes obtained from three Bayesian Sample size criteria (WOC, ACC, ALC) for both non-informative and informative priors. The WOC yields the largest sample size among ACC and ALC, regardless of the specified prior length and

type. The gap between optimal samples across criteria decreases as the specified length increases and as the prior moves from non-informative to informative. Optimal sample sizes obtained by ACC and ALC are closer to each other than those obtained by WOC, irrespective of the specified prior length and type. Also, the gap between WOC and other criteria (ACC and ALC) is wider when the specified length is greater than three compared to other sizes of specified lengths for all types of priors.

### 4.2. Discussion of the Findings

There are many uncertainties in Sample Size Determination (SSD), so approximate methods must be employed within any theoretical framework. This paper has explored some implications within a Bayesian framework for SSD, demonstrating that the approach is general and can be used to address many problems in statistical decision-making. The study found that typical non-informative prior distributions require large sample sizes. In contrast, a very informative prior distribution also leads to a minimal sample size when the prior mean is 'far' from the estimated value of the parameter. The sample sizes were largest when the prior distribution was very strongly concentrated around the estimated parameter value. These results have been shown both theoretically and numerically.

The primary objectives of the study were to illustrate the appropriate Bayesian methods (paradigm) for optimal sample size determination for estimation of disease (malaria) prevalence, to assess difference between optimal sample sizes obtained when using informative and non- informative prior's distributions and to assess difference among optimal sample sizes obtained when using Bayesian sample size performance metrics (ALC, ACC and WOC). The study has illustrated that appropriate Bayesian procedures for sample size determination include formulating a data model, selecting a prior distribution, observing data, constructing a likelihood function, constructing a posterior distribution and HPD, and finally calculating optimal sample sizes based on Bayesian Sample Size criteria by adjusting the highest posterior density.

The study found that, when using informative rather than non-informative prior distributions, the optimal sample size differs by almost 19% for the ACC and ALC criteria and by 2% for the WOC criterion. Also, the informative prior leads to smaller optimal sample sizes than a non-informative prior across all Bayesian Sample size criteria. This shows that using an informative prior distribution to determine the sample size yields a better estimate of the desired sample size.

Finally, the study found differences in the optimal sample sizes obtained using the Bayesian sample size criteria. When using an informative prior, the optimal sample sizes obtained via WOC are approximately 1.5 times larger than those obtained via ACC and ALC. Moreover, ACC's optimal sample size is, on average, 2% greater than ALC's. WOC yields an optimal sample size that is twice the ACC and ALC when using a non-informative prior. Also, ACC's optimal sample size is, on average, 3% larger than ALC's. The results concur with those of Brus et al. (2022): the fully Bayesian and mixed Bayesian-likelihood sample sizes were equal across all districts, and the mixed Bayesian-likelihood sample sizes were equal to the fully Bayesian sample sizes. The sample sizes were 234, 274, and 366 for ALC, ACC, and WOC, respectively (Cao et al., 2009).

## 5.0 Conclusion

The primary objective of this research was to illustrate appropriate Bayesian procedures for determining sample size in estimating disease prevalence. The results suggest that the optimal sample sizes obtained are not similar, not only because of the choice of prior parameters or the specified length, but also because of the choice between Bayesian sample-size performance metrics that average over the predictive distribution of the unknown data. The WOC criterion depends on the degree of risk that a researcher is willing to take in a study. The convention of reporting 95% intervals regardless of the data seems to favour ALC, since it provides a smaller sample size than WOC and ACC. Also, prior information can practically be utilised to improve Bayesian sample size estimation, as the estimated sample size decreases when moving from a non-informative to an informative prior.

## 6.0 Recommendations

Based on the study's findings, great attention is paid to the adoption and use of Bayesian sample size determination techniques with informative priors, as they yield sample sizes that are both sufficient and efficient for achieving a set of goals, as illustrated by the statistical simulation results.

The Bayesian approach provides greater predictive power than classical/frequentist methods. It uses probability to make a posterior decision under realistic parameter values by averaging over a designed prior, which is helpful for disease-prevalence research by region and time.

Also, it is recommended that the choice of Bayesian sample-size performance metrics remain a matter of individual curiosity or be determined by the particular situation. For instance, when it is significant to accommodate a possible, though unlikely, catastrophic data set, then WOC might be used. It is possible to compute sample sizes across a range of criteria and select a sample size and criterion based on information from all calculations.

This paper has presented a prospect for further study on the application of Bayesian techniques to determine optimal sample sizes in disease-prevalence studies when a single imperfect test is used. Consequently, the study has opened the door to further research on various applications of Bayesian methods, such as data mining and machine learning, for solving statistical problems, since the present study focused only on estimating the sample size to estimate the prevalence of the disease (Malaria). Therefore, the findings from this study may provide opportunities for other researchers to apply and develop Bayesian techniques across different areas, given recent advances in Bayesian computing algorithms. Also, more studies on Bayesian sample size should be conducted, particularly in tropical disease prevalence studies and those designed to estimate the sensitivity and specificity of diagnostic tests, to provide more room for the adoption of Bayesian statistical applications in real-world problems.

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