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Cross-sectional study to predict subnational levels of health workers' knowledge about severe malaria treatment in Kenya

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ABSTRACT

Objectives This study applied a Bayesian hierarchical ecological spatial model beyond predictor analysis to test for the best fitting spatial effects model to predict subnational levels of health workers' knowledge of severe malaria treatment policy, artesunate dosing, and preparation.

Setting County referral government and major faith-based hospitals across 47 counties in Kenya in 2019.

Design and participants A secondary analysis of cross-sectional survey data from 345 health workers across 89 hospitals with inpatient departments who were randomly selected and interviewed.

Outcome measures Three ordinal outcome variables for severe malaria treatment policy, artesunate dose and preparation were considered, while 12 individual and contextual predictors were included in the spatial models.

Results A third of the health workers had high knowledge levels on artesunate treatment policy; almost three-quarters had high knowledge levels on artesunate dosing and preparation. The likelihood of having high knowledge on severe malaria treatment policy was lower among nurses relative to clinicians (adjusted OR (aOR)=0.48, 95% CI 0.25 to 0.87), health workers older than 30 years were 61% less likely to have high knowledge about dosing compared with younger health workers (aOR=0.39, 95% CI 0.22 to 0.67), while health workers exposed to artesunate posters had 2.4-fold higher odds of higher knowledge about dosing compared with non-exposed health workers (aOR=2.38, 95% CI 1.22 to 4.74). The best model fitted with spatially structured random effects and spatial variations of the knowledge level across the 47 counties exhibited neighbourhood influence.

Conclusions Knowledge of severe malaria treatment policies is not adequately and optimally available among health workers across Kenya. The factors associated with the health workers' level of knowledge were cadre, age and exposure to artesunate posters. The spatial maps provided subnational estimates of knowledge levels for focused interventions.

Strengths and limitations of this study

- ► This study provided insights about health workers' knowledge levels and predictors influencing knowledge at subnational levels for focused interventions.
- ► The Bayesian modelling provided a robust methodology that combined multiple sources of information in a principled way to make reliable inferences.
- ► Due to multiple exploratory data analyses and comparisons, some of the results may have been significant by chance.
- ► The knowledge levels were self-reported by health workers working at the inpatient departments in the sampled hospitals and, therefore, should be generalised with caution.
- ► The study determined the health workers' level of knowledge about artesunate treatment but not their actual practice; hence, the results cannot be used to make inferences about actual clinical practice.

INTRODUCTION

Malaria is a major public health problem. In 2019, there were an estimated 229 million cases of malaria and 409 000 deaths due to malaria globally. The WHO African Region accounted for 94% of the malaria cases.[1] In 2020, the national malaria prevalence rate was 6% in Kenya. The prevalence varied across the five epidemiological zones, ranging from 19% in the Lake endemic zone to 0.4% in the low-risk malaria areas.[2]

Severe malaria is a medical emergency that requires prompt treatment, as it is associated with a high risk of death within the first 24 hours.[3] In 2012, the WHO recommended the use of parenteral artesunate for the treatment of severe malaria.[4] This treatment policy has been adopted and implemented across malaria-endemic countries in Africa.[3 4] Health workers' knowledge of evidence-based treatment recommendations is one of the basic requirements for a health-care system's readiness to implement any new drug policy.[5] In Kenya, concerted efforts have been made to support the WHO policy and monitor its implementation using various health facility surveys that report national levels, trends and predictors of artesunate

knowledge deficiencies among hospital health workers.[5 6] Similar cross-sectional studies have reported inadequate health workers' knowledge of artesunate-based treatment recommendations.[7 8] The data from these studies were multilevel and spatially correlated in nature. Traditionally, such data have been analysed by applying cluster adjustments and correlation matrices based on theoretical assumptions,[5 6 9–11] without considering spatial correlations between clusters.[12–14] Bayesian hierarchical spatial modelling accounts for correlation by introducing effects at different levels of a hierarchy to estimate random effects together with other model parameters accounting for variability within and between sites.[15–20] The random effects incorporated into fixed-effect models capture the heterogeneity across clusters in the regression coefficients, accounting for the dependence of observations from the same cluster,[21–24] leading to accurate conclusions.[25 26] The Bayesian multilevel models account for the spatial heterogeneity existing among groups, and the conditional autoregressive (CAR) models spatial autocorrelation based on neighbourhood relationships.[27–32] In this study, neighbourhood was defined using queen adjacency, where a county was considered a neighbour if it shared either a vertex or a node. In this study, a Bayesian hierarchical ecological spatial model beyond predictor analysis was applied to test for the best fitting model to predict subnational artesunate knowledge levels across 47 counties in Kenya.

METHODS

National standards and implementation context

Since 2012, the severe malaria treatment policy in Kenya recommends that all children and adults, including pregnant women in all trimesters, should be treated with parenteral artesunate.[3 4 33] Children weighing less than 20 kg should be given 3.0 mg/kg per dose of artesunate, while children weighing more than 20 kg and adults should receive 2.4 mg/kg of artesunate. Artesunate is dispensed as a powder of artesunic acid, which is dissolved in sodium bicarbonate (5%) to form sodium artesunate. The solution is then diluted using normal saline (0.9% sodium chloride) or 5% dextrose solution to make a concentration suitable for either intravenous or intramuscular administration. The supportive activities for implementing the treatment policy included a nationwide supply of artesunate, revision and dissemination of malaria treatment guidelines and job aids, and in-service training of front-line health workers on broader malaria case management with more in-depth information on the use and effectiveness of artesunate in managing severe malaria.[6]

Data sources

The manuscript presents a secondary data analysis of the cross-sectional cluster sample survey undertaken in 2019 to monitor the progress of the health systems' readiness and the quality of inpatient malaria management in Kenyan hospitals. The survey was undertaken at all 47 counties in Kenya, including a major government and faith-based hospital in every county. In each hospital, a randomly sampled clinician and nurse on duty in specific paediatric and medical wards of interest was surveyed (figure 1). Details of the methodologies have been previously published.[5] Of relevance for this paper, the interviews with health workers were undertaken by trained and experienced study nurses to establish demographic characteristics of the respondents, their exposure to supportive interventions, and knowledge about artesunate treatment using a self-administered multiple-choice questionnaire. The availability of medicines and job aids was assessed in hospital pharmacy and admission wards of interest.

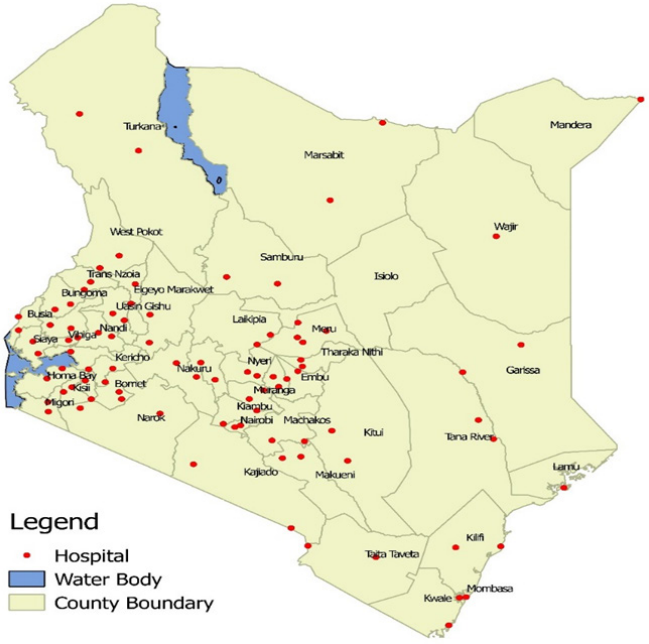

Figure 1 Map of survey hospitals.

Patient and public involvement statement

Patients and public were not involved in the design, execution, reporting or dissemination of this research.

Outcomes, definitions and factors examined

The study considered three response variables reflecting the correctness of the health workers' knowledge about recommended antimalarial treatment for severe malaria, artesunate dose and preparation. These variables were constructed using a multiple correspondence analysis (MCA) approach based on variables measured during the survey. MCA is a data analysis technique for nominal categorical data and is used to detect and represent underlying structures in a complex dataset.[34] Prior to computing the MCA, the health worker outcome variables were recoded into dichotomous variables, allowing the variables to take a value of zero or one. The resulting polytomous knowledge response was ordered on a three-point scale: high, medium or low. The definitions of the knowledge categories for each outcome assessed are listed in table 1.

Table 1 Categories of knowledge outcomes, national standards and study definitions

Knowledge outcomes	National recommendations	Knowledge categories	Category definitions
Treatment policy for severe malaria	Artesunate for the following three severe malaria populations: 1. children and non-pregnant adults; 2. pregnant women in first trimester; 3. pregnant women in second & third trimesters	High	Artesunate response for all three severe malaria populations
		Medium	Artesunate response for two severe malaria populations
		Low	Artesunate response for one or none of the populations
Artesunate dose	2 wt categories: ► 3 mg/kg for child <20 kg, ► 2.4 mg/kg for patient >20 kg	High	Correct response for 2 wt categories
		Medium	Correct response for one weight category
		Low	Incorrect responses for all the weight categories
Artesunate preparation	Solutions for two artesunate preparation steps: 1. bicarbonate for reconstitution 2. saline or 5% dextrose for dilution	High	Correct response for two preparation steps
		Medium	Correct response for one preparation step
		Low	Incorrect response for any of the preparation steps

The variables selected for analysis were based on previous studies[5] and classified as individual or contextual predictors. The health worker-level attributes were considered as individual predictors and they included: gender (male vs female), cadre (clinician vs nurse), age (21–30 vs 31–60), years of experience (<10 years vs >10 years), admission ward allocation (medical vs paediatric), artesunate training (yes vs no), access to malaria guidelines (yes vs no), and access to paediatric protocols (yes vs no). The contextual variables presented heath facility level characteristics, including availability of artesunate (yes vs no), display of artesunate administration posters (yes vs no), availability of artesunate dosing job aids (yes vs no) and malaria endemicity classification (high vs low).

Statistical analysis

Summary and exploratory analysis

Descriptive statistics were used to summarise the demographic characteristics of health workers and health facilities. Subsequently, applying the Bayesian approach, univariate analysis, estimated OR and credible intervals (CI) were calculated. Significant predictors (80% CI) associated with the level of health workers' knowledge of severe malaria treatment policy, artesunate dosing and preparation were identified and included in the multilevel modelling. Then, an ordinal logistic regression analysis adjusted for clustering at the county level was performed to estimate the effects of the predictor variable on the response variable (95% CI) by fitting three hierarchical models.

Bayesian method for ordinal logistic regression model

The ordinal logit model was developed from the general form of the binomial models. The model can be expressed as a latent variable model,[35 36] a powerful class of models for treating observations that fall into mutually exclusive categorical classes. The flexibility of this regression framework allows for better inferences. Initially, ordinal logistic regression analysis was implemented, followed by Bayesian hierarchical spatial modelling, as shown below:

Let Y_{ij} be a trichotomous outcome variable taking values 1, 2, or 3 if the jth health worker in the ith county $i = 1, \ldots, 47$ had low, medium or high artesunate knowledge, respectively.

In this study, three versions of the cumulative link model for ordinal-scale observations were fitted as follows:

$$\log\left(\frac{\gamma_{ijk}}{1-\gamma_{ijk}}\right) = \theta_k - \left(x_{ij}^T\beta + u_i + v_i\right), \quad i = 1, \ldots, 47,\ j = 1, \ldots, n_i,\ k = 1, 2, 3, \tag{1}$$

where

$$\gamma_{ijk} = P\left(Y_{ij} \le k\right) = \pi_{ij1} + \pi_{ij2} + \ldots + \pi_{ijk} \text{ with } \sum_{k=1}^{3} \pi_{ijk} = 1$$

are cumulative probabilities, x_{ij}^T is a p-vector of regression variables for the parameters, β without a leading column for an intercept; θ_k, $k = 0, 1, 2, 3$ are thresholds for the cumulative ordinal logit model; u_i is a spatial structured component random effect for the i–th county with a CAR distribution $u_i|\boldsymbol{u}_{-i} \sim N\left(\bar{u}_{\delta_i}, \frac{\sigma_u^2}{n_{\delta_i}}\right)$, where $\bar{u}_{\delta_i} = n_{\delta_i}^{-1} \sum_{j \in \delta_i} u_j \delta_i$ and n_{δ_i} represent the set of neighbours and the number of neighbours for the i–th county, respectively; and v_i is an unstructured spatial random effect for the i–th county defined as $v_i \sim N\left(0, \sigma_v^2\right)$. The first model and second models (*Model 1, Model 2*) were ordinal logistic regressions with spatially structured and unstructured random effects respectively, the third model (*Model 3*) was a convolution model fit by combining both structured and unstructured spatial random effects. Online supplemental information provides a more detailed description of the Bayesian hierarchical spatial modelling.

Bayesian statistical inference

During the model assessment, significant individual and contextual predictors were included in the model simultaneously. The predictive performance of the three hierarchical models was compared using the deviance information criterion (DIC), and a smaller DIC was regarded as a better model. Sensitivity analysis was performed by assuming three chains of Markov Chain Monte Carlo (MCMC) algorithms,[37] specifying the same model and prior information from different starting values and comparing the variance within each chain with the variance between chains. Large MCMC samples were used to establish better estimates. In executing this analysis, 10 000 iterations with a burn-in of 500 and thinning of one were run to reduce autocorrelation and avoid bias in the SE estimate of the posterior mean. Model convergence was assessed using trace plots, histograms and autocorrelation graphs, monitored by R-hat convergence diagnostic, which is the ratio of the spread of all the values combined with the mean spread of each chain. The posterior means/OR, quantiles, median, SD and the corresponding 95% CI were used to assess the significance of all parameters.[38] The spatial random effects from the best fitting model (structured, unstructured or convolution) of health workers with high knowledge of treatment policy, artesunate dosing and preparation were overlaid on a map showing all counties in Kenya. Initial analysis was conducted using StataCorp V.14 (Stata Statistical Software: Release 14. College Station, TX, StataCorp LP). The Bayesian models were fitted using the R2OpenBUGS statistical package.

RESULTS

Health worker characteristics

Of the 345 interviewed health workers, most were female (59.7%), aged 21–30 years (62%), with less than 10 years of inpatient experience (82.6%), and working in low malaria risk areas (72.5%). A quarter of them (24.6%) had access to dosing job aids, 36.8% had been trained on artesunate use and 40.9% had access to malaria treatment guidelines. Most of the health workers worked at hospitals with artesunate in stock (90.7%) and displayed artesunate administration posters (82.9%). The health worker ward allocation, cadre and paediatric protocol exposures were similarly distributed in the sample (table 2).

Table 2 Distribution of the health workers' characteristics

	N=345	
	n	Per cent (%)
Predictor variables		
Gender		
Male	139	40.3
Female	206	59.7
Health worker cadre		
Clinician	159	46.1
Nurse	186	53.9
Age		
21–30	214	62.0
31–60	131	38.0
Years of experience		
>10 years	60	17.4
<10 years	285	82.6
Ward allocation		
Medical	170	49.3
Paediatric	175	50.7
Exposure to artesunate interventions		
Trained on artesunate	127	36.8
Malaria treatment guidelines	141	40.9
Paediatric protocol	186	53.9
Artesunate poster	286	82.9
Artesunate dosing wheel	85	24.6
Availability of artesunate	313	90.7
Endemicity		
Low	250	72.5
High	95	27.5

Health workers level of knowledge on severe malaria treatment policy, artesunate dose and preparation

The reliability of the indices constructed by the MCA approach was assessed using Cronbach's alpha coefficient and a score of >0.7 indicated high intracorrelation among a set of variables.[34] The Cronbach alpha coefficients for knowledge about severe malaria treatment policy, artesunate dosing and preparation were 0.7674, 0.8901 and 0.7810, respectively. The resulting polytomous knowledge response was ordered as high, medium, or low.

A third of the health workers had a high level of knowledge about artesunate treatment policy for severe malaria (32.8%), while 73.9% and 70.9% of health workers had high levels of knowledge about the recommended artesunate dosing and preparation, respectively (table 3). Online supplemental tables 1-3 show the results of univariate ordinal logistic regression analyses examining the association between 12 factors and three knowledge outcomes. Of the 12 factors examined, 2, 10 and 1 factor(s) met the inclusion criteria for multivariable analysis (80% CI) with knowledge about treatment policy, artesunate dosing and artesunate preparation, respectively.

Table 4 reports the results of the three comparative hierarchical models that were fitted in multivariable analysis and their goodness of fit is compared using DIC. For the health workers' knowledge on treatment policy, the DIC for model 1, model 2 and model 3 were 762.71, 780.17 and 770.14, respectively. Regarding health workers' knowledge on artesunate dosing, the DIC for model 1, model 2 and model 3 were 488.83, 496.19 and 497.80, respectively. For the health workers' knowledge

Table 3 Knowledge levels about artesunate treatment

Distribution of outcome variables		
	N=345	
Knowledge categories	n	Per cent (%)
Treatment policy		
High	113	32.8
Medium	107	31.0
Low	125	36.2
Dosing		
High	255	73.9
Medium	57	16.5
Low	33	9.6
Artesunate preparation*		
High	244	70.9
Medium	85	24.7
Low	15	4.4

*has one missing value.

on artesunate preparation, the DIC for model 1, model 2 and model 3 were 503.31, 510.17 and 507.31, respectively. Model 1 with spatially structured random effects provided a better fit for the three outcomes. Spatially structured random effects illustrate the necessity of accounting for spatial autocorrelation, which, if ignored in the regression model, can lead to biased inferences.

The posterior means/OR, quantiles, median, SD and the corresponding 95% CI were used to assess the significance of all parameters. The posterior estimates were similar across the three hierarchical models and the adjusted ORs and 95% CI estimates from the best fitting model are reported. For the outcome on the knowledge about artesunate treatment policy, the health workers' cadre was the only significant predictor. The likelihood of having a high knowledge of severe malaria treatment policy was significantly lower in nurses than in clinicians (aOR=0.59, 95% CI 0.40 to 0.89). Regarding knowledge of the recommended artesunate dosing, health worker cadre, age and exposure to artesunate administration poster were significant predictors. Nurses were 52% less likely to have high knowledge about dosing compared with the clinicians (aOR=0.48, 95% CI 0.25 to 0.87). Health workers older than 30 years were 61% less likely to have high knowledge about dosing compared with younger health workers (aOR=0.39, 95% CI 0.22 to 0.67), while health workers exposed to artesunate posters had 2.4-fold increased odds of higher knowledge about dosing compared with non-exposed health workers (aOR=2.38, 95% CI 1.22 to 4.74). Finally, based on unadjusted univariate analysis (online supplemental table 3), the health workers who had access to an artesunate dosing wheel were 57% more likely to have higher knowledge of artesunate preparation compared with those who did not have access (OR=1.57, 80% CI 1.09 to 2.30). However, the same predictor variable lost significance at the 95% CI, adjusted for multivariable analysis (aOR=1.58, 95% CI 0.91 to 2.88), refer to online supplemental table 4.

Model 1: spatially structured random effects; model 2: spatially unstructured random effects; model 3: convolution

Figures 2–4 show the spatial random effects of the posterior means of the probability of health workers having high knowledge of severe malaria treatment policy, artesunate dosing and preparation, respectively, overlaid on a map showing all counties in Kenya. The deep red colour denotes regions with strictly high knowledge, while the light red colour denotes strictly low knowledge. In figure 2, the health workers in Kisii county had high knowledge levels (>10%) on severe malaria treatment policy, while those in Nyandarua, Nyamira, Laikipia and Mandera counties had low knowledge levels (<10%). In figure 3, the health workers in Muranga, Kisii, Embu, Uasin Gishu, Kiambu and Kisumu counties had high knowledge levels (>10%) about artesunate doses, while those in Nyandarua, Nyamira, Garissa, Busia and Nairobi counties had low knowledge levels (<10%). In figure 4, there were 17 counties with high knowledge levels (>10%), while 16 counties had low knowledge levels (<10%), on artesunate preparation.

DISCUSSION

This study applied Bayesian hierarchical ecological spatial modelling as an extension to the standard approach to examine the spatial effects at the national level on Kenyan health workers' knowledge of severe malaria treatment policy, artesunate dosing and preparation. Three ordinal response variables for severe malaria treatment policy, artesunate dose and preparation were considered, while 12 individual and contextual predictors were included in the models. The analysis was performed using three different models: the first model was ordinal logistic regression with spatially structured random effects, the second model with spatially unstructured random effects and the third with convolution. This Bayesian approach provided another way of examining factors associated with health workers' level of knowledge and the spatial factors around severe malaria treatment policies for targeted malaria interventions.

Knowledge required to treat severe malaria is not adequately and optimally spread among all health workers at the national level. A third of the health workers had high knowledge levels about WHO's artesunate treatment policy. Previous studies have reported similar findings.[5 6 8] This was linked to the low knowledge levels on the treatment policy for pregnant women in the first and second trimesters. Almost three-quarters of health workers had high knowledge levels on the correct artesunate dosing recommendations for patients weighing both below and above 20 kg and were aware of both artesunate preparation solutions. The majority of health workers have not been trained on artesunate treatment policy. There is a need to organise more training avenues, such as seminars

Table 4 Bayesian approach to multivariate ordinal logistic regression using OR, 95% credible Interval (CI)

		Posterior summary estimates based on 2.5% and 97.5% posterior quantiles								
		Knowledge on severe malaria treatment policy			Knowledge on artesunate dose			Knowledge on artesunate preparation		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	N	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Fixed effects										
Health worker cadre										
Clinician	159	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)			
Nurse	186	**0.59 (0.40 to 0.89)**	0.58 (0.39 to 0.86)	0.58 (0.38 to 0.87)	**0.48 (0.25 to 0.87)**	0.48 (0.26 to 0.88)	0.47 (0.26 to 0.87)			
Age										
21–30	214				1 (Ref)	1 (Ref)	1 (Ref)			
31–60	131				**0.39 (0.22 to 0.67)**	0.39 (0.23 to 0.68)	0.39 (0.22 to 0.67)			
Artesunate poster										
No	59				1 (Ref)	1 (Ref)	1 (Ref)			
Yes	286				**2.38 (1.22 to 4.74)**	2.33 (1.18 to 4.63)	2.44 (1.22 to 4.91)			
Artesunate dosing wheel										
No	260				1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)
Yes	85				1.92 (0.97 to 4.04)	1.94 (0.97 to 3.98)	1.91 (0.95 to 4.01)	1.58 (0.91 to 2.88)	1.57 (0.90 to 2.85)	1.58 (0.92 to 2.83)
Random effects										
Spatially structured (τu)		313.20 (1.36 to 5185.57)		480.80 (2.13 to 5184.00)	423.15 (1.24 to 5431.52)		482.00 (0.60 to 4948.05)	549.40 (6.96 to 4847.67)		561.90 (7.37 to 5257.57)
Spatially unstructured (τv)			111.85 (2.62 to 5093.05)	331.50 (3.85 to 3790.10)		411.55 (2.51 to 4587.05)	667.75 (12.17 to 5402.00)		419.55 (11.14 to 4565.10)	380.60 (7.23 to 4330.00)
Model fit										
DIC (PD)		**762.71 (20.34)**	780.17 (40.90)	770.14 (29.31)	**488.83 (21.76)**	496.19 (29.86)	497.80 (33.04)	**501.22 (4.4)**	**502.38 (6.29)**	504.25 (8.88)

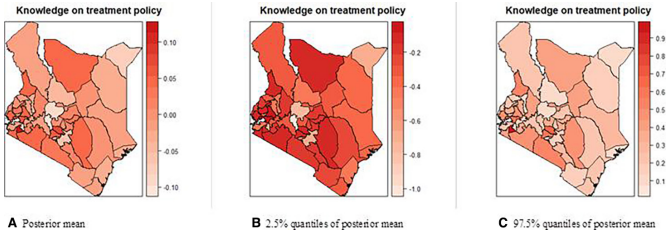

Figure 2 Spatially structured random effects on probability of health workers having high knowledge on the recommended treatment policy of severe malaria using artesunate. (A) Posterior mean, (B) 2.5% quantiles and (C) 97.5% quantiles.

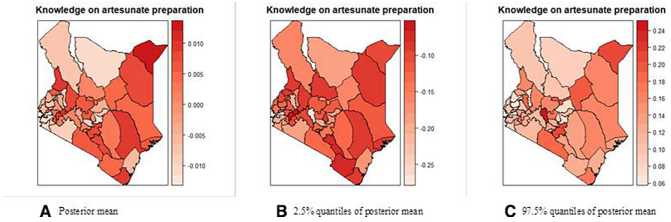

Figure 4 Spatially structured random effects on probability of health workers having high knowledge on artesunate preparation. (A) Posterior mean, (B) 2.5% quantile and (C) 97.5% quantile.

and workshops, and to re-evaluate the mode of delivery of training conducted in the past.

Nurses were less likely than clinicians to have a high level of knowledge of the WHO treatment policy for severe malaria, consistent with other research findings.[8 39] There is a need for interprofessional collaboration and innovative measures to improve knowledge of the severe malaria treatment policy and dosing among nurses in future case management training. The health workers above 30 years of age had low knowledge of artesunate dosing. These health workers are a critical segment of the workforce and should be targeted for refresher training on severe malaria case management. It is commendable that the artesunate poster contributes to health workers' level of knowledge of artesunate dosing. A similar observation was made in Tanzania that healthcare workers relied on posters to prepare injectable artesunate.[8] The programme should continue updating, printing and disseminating more posters to all health facilities to supplement the knowledge gained through training.

There is evidence of spatially structured variation in health workers' knowledge of severe malaria treatment policy, artesunate dosing and preparation at various county hospitals. The best fitting model for severe malaria treatment policy, artesunate dosing and preparation was fitted with spatially structured random effects. The similarity of responses from health workers interviewed in a given facility and the likelihood of similarity between health facility structures across adjacent counties explain the neighbourhood influence on the spatially structured models. The substantial heterogeneity among the health workers with high knowledge of treatment policy, artesunate dosing and preparation at the county level showed that severe malaria management may differ from one health facility or county to another due to unobserved heterogeneity, and this required Bayesian hierarchical model to account for clustering within health facilities and counties.[40] Bayesian hierarchical spatial models account for both the nesting of health workers within health facilities (vertical dependence) and the spatial autocorrelation among the counties (horizontal dependence) by assigning a normal CAR prior to the random effects.[41 42] Bayesian spatial models incorporate geographical correlation by a CAR prior to assess small area variations and map spatial patterns.[43] The models assume that geographically proximate spatial units tend to have similar risks, illustrating the necessity of accounting for spatial variation across the counties for precise inferences. The spatially unstructured random variables ignore the geographical location of the analysis units by capturing the unobserved non-spatial heterogeneity.[44–46] The spatial maps provide subnational knowledge level estimates that can be used for focused interventions.

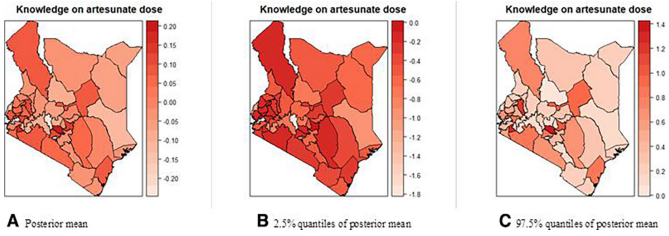

Figure 3 Spatially structured random effects on probability of health workers having high knowledge on artesunate dose. (A) Posterior mean, (B) 2.5% quantiles, and (C) 97.5% quantiles.

Strengths and limitations

This study provided insights into health workers' knowledge levels and predictors influencing knowledge at subnational levels for focused interventions. Bayesian modelling provided a robust methodology that combined multiple sources of information in a principled way to perform reliable inferences. This study has a few limitations. First, due to multiple exploratory data analyses and comparisons, some of the results may have been significant by chance. Second, the knowledge levels were self-reported by health workers working in the inpatient departments at the sampled hospitals and should be generalised with caution. Third, the study determined the health workers' level of knowledge on artesunate treatment but not their actual practice; hence, the results cannot be extended to infer about actual clinical practice.

CONCLUSION

The individual factors associated with health workers' knowledge of severe malaria treatment policy, dosing and preparation were health worker cadre and age, while exposure to artesunate posters was a contextual factor. At the health facility level, various targeted strategies such as

job training, continuous medical education with a multidisciplinary approach, and case management training with emphasis on dosing should be explored to improve the knowledge base of health workers for severe malaria management. Continued routine dissemination of information and display of artesunate posters to health facilities is encouraged.

Based on the spatial maps, the National Malaria Programme can focus interventions with a multidisciplinary approach to bridge the knowledge gaps identified at the subnational level. Bayesian methodology can be adopted to analyse health survey data with similar structures and settings. A qualitative study is recommended to uncover why the current operational interventions have not improved health workers' knowledge of the severe malaria treatment policy.

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Supplementary files

Supplementary Information (SI): Bayesian hierarchical spatial modelling

Initially, ordinal logistic regression analysis was implemented followed by Bayesian hierarchical spatial modelling.

Let Y_{ij} be a trichotomous outcome variable taking values 1, 2 or 3 if the *j*-th health worker in the *i*-th county $i = 1, \dots, 47$ had low, medium or high artesunate knowledge, respectively.

This variable is a categorized version of a continuous latent (utility) variable defined by

$$Z_{ij} = \eta + \varepsilon_{ij}, \quad (1)$$

where η is a predictor depending on covariates and parameters and ε_{ij} is the error term. The two variables Y_{ij} and Z_{ij} are linked by $Y_{ij} = k$ if and only if

$$\theta_{k-1} < Z \leq \theta_k, k = 1,2,3,$$

with thresholds $-\infty < \theta_0 < \theta_1 < \theta_2 < \theta_3 < \infty$. In a multinomial logit model setting, the error variables in (1) are independent across the categories and assumed to be standard extreme value distributed with function F. Hence, it follows that Y_{ij} obeys a cumulative logit model. The predictor is then defined as:

$$P(Y_{ij} \leq k|\eta) = F(\theta_k - \eta). \quad (2)$$

If F in equation (3) is chosen to be the logistic distribution function, the influence of covariates is modelled using the multinomial logit model given as:

$$P(Y_{ij} = k|Y_{ij} \geq k, \eta) = \frac{\exp(\eta)}{1 + \exp(\eta)} = \theta_k - \eta. \quad (3)$$

In this study, the following 3 versions of this cumulative link model for ordinal-scaled observation were implemented as:

$$\text{Model 1: } \log\left(\frac{\gamma_{ijk}}{1-\gamma_{ijk}}\right) = \theta_k - \left(x_{ij}^T\beta + u_i\right), \qquad i = 1,\dots,47, j = 1,\dots,n_i, k = 1,2,3, \quad (4)$$

$$\text{Model 2: } \log\left(\frac{\gamma_{ijk}}{1-\gamma_{ijk}}\right) = \theta_k - \left(x_{ij}^T\beta + v_i\right), \qquad i = 1,\dots,47, j = 1,\dots,n_i, k = 1,2,3, \quad (5)$$

$$\text{Model 3: } \log\left(\frac{\gamma_{ijk}}{1-\gamma_{ijk}}\right) = \theta_k - \left(x_{ij}^T\beta + u_i + v_i\right), i = 1,\dots,47, j = 1,\dots,n_i, k = 1,2,3, \quad (6)$$

where,

$$\gamma_{ijk} = P\left(Y_{ij} \le k\right) = \pi_{ij1} + \pi_{ij2} + \cdots + \pi_{ijk}\ with \sum_{k=1}^{3} \pi_{ijk} = 1$$

are cumulative probabilities, η is the linear predictor and x_{ij}^T is a *p*-vector of regression variables for the parameters, β without a leading column for an intercept and F is the inverse link function; $\theta_k, k = 0,1,2,3$ are thresholds for cumulative ordinal logit model, u_i is a spatial structured component random effect for the $i-$th county with a conditional autoregressive (CAR) distribution $u_i|\boldsymbol{u}_{-i} \sim N\left(\bar{u}_{\delta_i}, \frac{\sigma_u^2}{n_{\delta_i}}\right)$, where $\bar{u}_{\delta_i} = {n_{\delta_i}}^{-1}\sum_{j\in\delta_i} u_{j,}$ δ_i and n_{δ_i} represent the set of neighbors and the number of neighbors for the $i-$th county respectively; and v_i is an unstructured spatial random effect for the $i-$th county defined as $v_i \sim N(0, \sigma_v^2)$.

The first model (*Model 1*) was ordinal logistic regression with spatially structured random effects; the second model (*Model 2*) with unstructured spatially random effects and the third (*Model 3*), a convolution model, was fit by combining both unstructured and structured spatial random effects.

In implementing Bayesian analysis, a set of posterior means of the relative risks was then used to create maps to visualize the high to low health workers knowledge levels by borrowing information from all health workers.

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Supplementary files

Supplementary Table 1. Distribution of the predictor variable in relation to the health workers knowledge on malaria treatment policy with univariate ordinal logistic regression

	Knowledge on severe malaria treatment policy				
	N	**High**	**Medium**	**Low**	**OR(80%Credible Interval)**
Gender					
Male	139	48(34.5)	42(30.2)	49(35.3)	1 (ref)
Female	206	65(31.6)	65(31.6)	76(36.9)	0.87(0.68;1.14)
Health worker cadre					
Clinician	159	63(39.6)	47(29.6)	49(30.9)	1(ref)
Nurse	186	50(26.9)	60(32.3)	76(40.9)	**0.57(0.44;0.73)**
Age					
21-30	214	68(31.8)	72(33.6)	74(34.6)	1 (ref)
31-60	131	45(34.4)	35(26.7)	51(38.9)	0.90(0.69;1.17)
Years of experience					
>10years	60	17(28.3)	19(31.7)	24(40)	1 (ref)
<10years	285	96(33.7)	88(30.9)	101(35.4)	0.77(0.53;1.09)
Ward allocation					
Medical	170	55(32.4)	49(28.8)	66(38.8)	1 (ref)
Paediatric	175	58(33.1)	58(33.1)	59(33.7)	1.09(0.85;1.40)
Trained on artesunate					
No	218	68(31.2)	62(28.4)	88(40.4)	1 (ref)
Yes	127	45(35.4)	45(35.4)	37(29.1)	**1.42(1.08;1.87)**
Malaria treatment guidelines					
No	204	67(32.8)	55(27)	82(40.2)	1 (ref)
Yes	141	46(32.6)	52(36.9)	43(30.5)	1.00(0.76;1.29)
Paediatric protocol					
No	159	52(32.7)	44(27.7)	63(39.6)	1 (ref)
Yes	186	61(32.8)	63(33.9)	62(33.4)	1.18(0.91;1.54)
Exposure of artesunate poster					
No	59	22(37.3)	18(30.5)	19(32.2)	1 (ref)
Yes	286	91(31.8)	89(31.1)	106(37)	0.75(0.52;1.06)
Access of artesunate dosing wheel					
No	260	85(32.7)	78(30)	97(37.3)	1 (ref)
Yes	85	28(32.9)	29(34.1)	28(32.9)	1.20(0.89;1.60)
Availability of artesunate					
No	32	12(37.5)	7(21.9)	13(40.7)	1 (ref)
Yes	313	101(32.3)	100(31.9)	112(35.8)	0.95(0.61;1.55)
Endemicity					
Low	250	78(31.2)	75(30)	97(38.8)	1 (ref)
High	95	35(36.8)	32(33.7)	28(29.5)	1.27(0.95;1.70)

Supplementary Table 2. Distribution of the predictor variable in relation to the health workers knowledge on artesunate dosing with univariate ordinal logistic regression

Knowledge on artesunate dose					
	N	**High**	**Medium**	**Low**	**OR(80% Credible Interval (CI)**
Gender					
Male	139	109(78.4)	20(14.4)	10(7.2)	**1 (ref)**
Female	206	146(70.9)	37(18)	23(11.2)	**0.63(0.45; 0.87**)
Health worker cadre					
Clinician	159	134(84.3)	16(10.1)	9(5.7)	1 (ref)
Nurse	186	121(65.1)	41(22)	24(12.9)	**0.33(0.24; 0.47)**
Age					
21-30	214	173(80.8)	30(14)	11(5.1)	**1 (ref)**
31-60	131	82(62.6)	27(20.6)	22(16.8)	**0.34(0.24; 0.47)**
Years of experience					
>10years	60	33(55)	12(2.0)	15(25)	**1 (ref)**
<10years	285	222(77.9)	45(1.8)	18(6.3)	**1.58(1.05; 2.35)**
Ward allocation					
Medical	170	118(69.4)	34(20)	18(10.6)	**1 (ref)**
Paediatric	175	137(78.3)	23(13.1)	15(8.6)	**1.58(1.16; 2.17)**
Trained on artesunate					
No	218	158(72.5)	38(17.4)	22(10.1)	1 (ref)
Yes	127	97(76.4)	19(15)	11(8.7)	1.17(0.85; 1.64)
Malaria treatment guidelines					
No	204	146(71.6)	33(16.2)	25(12.3)	1 (ref)
Yes	141	109(77.3)	24(17)	8(5.7)	1.39(0.98; 1.93)
Paediatric protocol					
No	159	102(64.2)	37(23.3)	20(12.6)	1 (ref)
Yes	186	153(82.3)	20(10.8)	13(7)	**1.68(1.22; 2.29)**
Exposure of artesunate poster					
No	59	32(54.2)	15(25.4)	12(20.3)	**1 (ref)**
Yes	286	223(78)	42(14.7)	21(7.3)	**3.00(2.09; 4.37)**
Access of artesunate dosing wheel					
No	260	183(70.4)	48(18.5)	29(11.2)	**1 (ref)**
Yes	85	72(84.7)	9(10.6)	4(4.7)	**2.52(1.66; 4.01)**
Availability of artesunate					
No	32	16(50)	9(28.1)	7(21.9)	**1 (ref)**
Yes	313	239(76.4)	48(15.3)	26(8.3)	**3.07(1.97; 5.09)**
Endemicity					
Low	250	176(70.4)	44(17.6)	30(12)	**1 (ref)**
High	95	79(83.2)	13(13.7)	3(3.2)	**2.09(1.41; 3.13)**

Supplementary Table 3. Distribution of the predictor variable in relation to the health workers knowledge on artesunate preparation with univariate ordinal logistic regression

Knowledge on artesunate preparation					
	N	High	Medium	Low	OR(80% Credible Interval (CI)
Gender					
Male	139	95(68.3)	32(23)	12(8.6)	**1 (ref)**
Female	205	149(72.7)	53(25.9)	3(1.5)	1.27(0.93;1.75)
Health worker cadre					
Clinician	159	111(69.8)	39(24.5)	9(5.7)	1 (ref)
Nurse	185	133(71.9)	46(24.9)	6(3.2)	1.12(0.83;1.52)
Age					
21-30	214	153(71.5)	54(25.2)	7(3.3)	1 (ref)
31-60	130	91(70)	31(23.8)	8(6.2)	0.82(0.60;1.13)
Years of experience					
>10years	59	44(74.6)	14(23.7)	1(1.7)	1 (ref)
<10years	285	200(70.2)	71(24.9)	14(4.9)	0.77(0.50;1.16)
Ward allocation					
Medical	170	116(68.2)	46(27.1)	8(4.7)	1 (ref)
Paediatric	174	128(73.6)	39(22.4)	7(4)	1.29(0.95;1.77)
Trained on artesunate					
No	217	156(71.9)	50(23)	11(5.1)	1 (ref)
Yes	127	88(69.3)	35(27.6)	4(3.1)	0.90(0.66;1.23)
Malaria treatment guidelines					
No	203	135(66.5)	59(29.1)	9(4.4)	1 (ref)
Yes	141	109(77.3)	26(18.4)	6(4.3)	1.34(0.98;1.83)
Paediatric protocol					
No	159	105(66)	46(28.9)	8(5)	1 (ref)
Yes	185	139(75.1)	39(21.1)	7(3.8)	0.81(0.60;1.10)
Exposure of artesunate poster					
No	59	40(67.8)	17(28.8)	2(3.4)	1 (ref)
Yes	285	204(71.6)	68(23.9)	13(4.6)	1.19(0.79;1.76)
Access of artesunate dosing wheel					
No	259	179(69.1)	66(25.5)	14(5.4)	1 (ref)
Yes	85	65(76.5)	19(22.4)	1(1.2)	**1.57(1.09;2.30)**
Availability of artesunate					
No	32	21(65.6)	9(28.1)	2(6.3)	1 (ref)
Yes	312	223(71.5)	76(24.4)	13(4.2)	1.29(0.77;2.15)
Endemicity					
Low	249	176(70.7)	64(25.7)	9(3.6)	1 (ref)
High	95	68(71.6)	21(22.1)	6(6.3)	0.97(0.69;1.38)

Supplementary files

Supplementary Table 4. Bayesian approach to multivariate ordinal logistic regression using odds ratio (OR), 95% Credible Interval (CI)

		Posterior summary estimates based on 2.5% and 97.5% posterior quantiles								
		Knowledge on severe malaria treatment policy			**Knowledge on artesunate dose**			**Knowledge on artesunate preparation**		
		Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
	N	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**
Fixed effects										
Gender										
Male	139				1 (Ref)	1 (Ref)	1 (Ref)			
Female	206				0.84(0.45; 1.53)	0.85(0.48; 1.50)	0.84(0.45; 1.58)			
Health worker cadre										
Clinician	159	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)			
Nurse	186	**0.59(0.40; 0.89)**	0.58(0.39; 0.86)	0.58(0.38; 0.87)	**0.48(0.25; 0.87)**	0.48(0.26; 0.88)	0.47(0.26; 0.87)			
Age										
21-30	214				1 (Ref)	1 (Ref)	1 (Ref)			
31-60	131				**0.39(0.22; 0.67)**	0.39(0.23; 0.68)	0.39(0.22; 0.67)			
Years of experience										

>10years	60				1 (Ref)	1 (Ref)	1 (Ref)			
<10years	285				1.11(0.57; 2.13)	1.10(0.55; 2.29)	1.12(0.60; 2.22)			
Ward allocation										
Medical	170				1 (Ref)	1 (Ref)	1 (Ref)			
Paediatric	175				1.54(0.91; 2.60)	1.53(0.92; 2.63)	1.53(0.89; 2.54)			
Trained on artesunate										
No	218	1 (Ref)	1 (Ref)	1 (Ref)						
Yes	127	1.38(0.91; 2.08)	1.36(0.89; 2.04)	1.37(0.92; 2.07)						
Malaria treatment guidelines										
No	204									
Yes	141									
Paediatric protocol										
No	159				1 (Ref)	1 (Ref)	1 (Ref)			
Yes	186				1.27(0.76; 2.21)	1.29(0.75; 2.18)	1.29(0.74; 2.19)			
Artesunate poster										
No	59				1 (Ref)	1 (Ref)	1 (Ref)			
Yes	286				**2.38(1.22; 4.74)**	2.33(1.18; 4.63)	2.44(1.22; 4.91)			
Artesunate dosing wheel										

No	260				1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)	1 (Ref)
Yes	85				1.92(0.97; 4.04)	1.94(0.97; 3.98)	1.91(0.95; 4.01)	1.58(0.91; 2.88)	1.57(0.90; 2.85)	1.58(0.92; 2.83)
Availability of artesunate										
No	32				1 (Ref)	1 (Ref)	1 (Ref)			
Yes	313				1.94(0.81; 4.35)	2.03(0.81; 4.52)	1.80(0.70; 4.03)			
Endemicity										
Low	250				1 (Ref)	1 (Ref)	1 (Ref)			
High	95				1.58(0.78; 3.24)	1.61(0.84; 3.24)	1.53(0.69; 3.12)			
Random effects										
Spatially structured (τu)		313.20(1.36; 5185.57)		480.80(2.13;5184.00)	423.15(1.24;5431.52)		482.00(0.60;4948.05)	549.40(6.96;4847.67)		561.90(7.37;5257.57)
Spatially unstructured (τv)			111.85(2.62;5093.05)	331.50(3.85;3790.10)		411.55(2.51;4587.05)	667.75(12.17;5402.00)		419.55(11.14;4565.10)	380.60(7.23; 4330.00)
Model fit										
DIC (PD)		**762.71 (20.34)**	780.17 (40.90)	770.14 (29.31)	**488.83 (21.76)**	496.19 (29.86)	497.80 (33.04)	**501.22 (4.4)**	**502.38 (6.29)**	504.25 (8.88)

Model 1: Spatially structured random effects; Model 2: Spatially unstructured random effects; Model 3: Convolution