Beyond insecticide treated bed nets coverage to heterogeneous human behaviors and spatial realities

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Introduction: Insecticide-treated bed nets (ITNs) are a cost-efficient prevention method used to prevent malaria, yet their use in poorly urbanized and slum areas remains low. For instance, in these areas in Accra, Ghana, less than 2% of children sleep under fully functional ITNs. Thus, the expected drop in malaria prevalence in Accra and the rest of the country is still much below target. This study deconstructs urban malaria dynamics, revealing the complex interplay of ITNs, spatial heterogeneity, and human behaviors.

Methods: We evaluated urban malaria prevention knowledge, developed a metapopulation framework aligned with empirical findings, and incorporated behavior scenarios to understand urban malaria dynamics better.

Results: Our findings revealed that owning an ITN does not ensure its use, especially in densely populated areas. Limited living space and repurposing are identified as key barriers in Accra, Ghana, with healthcare visits emerging as catalysts for ITN use. Mathematical models incorporating spatial and demographic factors emphasize achieving 60% ITN use in each community patch for epidemic elimination. Our model emphasizes that while ITN use is a crucial intervention in malaria control, it alone may not significantly reduce malaria prevalence without considering spatial, demographic, and behavioral factors.

Discussion: To maximize the effectiveness of ITNs and significantly reduce malaria prevalence, decision-making processes must address the underlying reasons for late or nonadoption of the intervention. Therefore, we strongly recommend prioritizing targeted, one-onone sensitization campaigns, ensuring that barriers to ITN adoption are effectively identified and mitigated.

1 Introduction

The female mosquito, as the primary vector for numerous deadly infectious diseases, is considered the deadliest animal and is responsible for more than a million deaths per year (Prudêncio, 2020). These diseases include Chikungunya, Zika, Dengue, West Nile, Yellow fever, filariasis, and most notably, malaria, which continues to be the leading cause of mortality and morbidity, particularly in sub-Saharan Africa (SSA). For approximately two decades, malaria mortality rates saw a remarkable 67% decrease by the early 2020s (World Health organization, 2020). This achievement was attributed to the implementation of preventive measures such as indoor residual spraying (IRS), distribution of insecticide-treated bed nets (ITNs), and artemisinin-based combination therapy (ACT).

However, the onset of the global COVID-19 pandemic in early 2020 disrupted malaria control programs, notably impacting the distribution of ITNs (Aguma et al., 2023). This disruption had severe consequences for malaria-induced deaths in SSA, paralleling previous observations during the Ebola outbreak in West Africa in 2017 (Sherrard-Smith et al., 2020; World Health Organization, 2020; Aborode et al., 2021). Indeed, the anticipated 627,000 deaths from malaria surpass those linked to SARS-CoV-19 in Sub-Saharan Africa as a result of the suspension of ITN distribution efforts in 2019 (World Health organization, 2020; Ahmed et al., 2022; WHO, 2022). In addition to this risk posed by COVID-19 disruption, the invasion of *Anopheles stephensi*, described as a more competent vector of malaria-transmitting urban malaria, is magnifying malaria risk, as seen by the expanding evidence of this species invasion in Africa (Ahmed et al., 2022; Hemming-Schroeder and Ahmed, 2023).

ITNs infused with synthetic pyrethroids represent a leading non-pharmaceutical intervention in malaria control, significantly reducing malaria vectors and *Plasmodium* parasitemia in SSA (Lengeler, 2004; Lim et al., 2011). Since 2007, Ghana has initiated an extensive ITN distribution policy that reached ITN coverage of 85% in 2017 (Awine et al., 2017). Even with their cost efficiency, ITNs remain underutilized: fewer than 2% of children rest under fully operational ITNs (Elder et al., 2011), and in 2011, less than 40% of ITN-owning households in Accra, Ghana, consistently utilized them (Elder et al., 2011; Ahorlu et al., 2019). Although a more recent study indicated a slight rise in the usage rate of ITNs, it remains moderate in Ghana. Specifically, the ITN usage among children under five was only 54%, while the reported rate of ITN utilization in this group was estimated at approximately 61.88% in the Volta Region, Ghana (Orish et al., 2021) and between 21 to 43% nationwide from 2008 to 2021 (Klu et al., 2022). The primary factors contributing to this underuse include rapid physical and chemical degradation and frequent repurposing of ITNs (Ngonghala et al., 2014; Scates et al., 2020). The ramifications of not utilizing ITNs in the context of household net use behavior remain an underexplored facet in malaria research. While numerous studies have delved into the effectiveness on ITNs for malaria prevention, a substantial gap persists in investigating the direct consequences of decisions related to ITN usage and non-usage of the dynamics of malaria. This gap underscores the need for comprehensive research that specifically probes the intricate relationship between household net use behavior and their profound impact on the progression of malaria (Elder et al., 2011; Ahorlu et al., 2019).

Mathematical models have played a pivotal role in understanding disease dynamics and guiding policy decisions (Ross, 1902; Ross, 1911; Macdonald, 1950) and documenting policies for disease management (Heesterbeek et al., 2015). Such models have also been instrumental in designing vector control strategies and vaccination thresholds and assessing the effectiveness of ITNs (Ross, 1902; Ross, 1911; Elder et al., 2011). The basic reproductive number (R_0), a metric quantifying the average number of secondary infections produced by single infected individuals in a completely susceptible population, assesses the potential for disease transmission and evaluates the likelihood of an outbreak. Thus, R_0 remains a metric for assessing the magnitude of an epidemic. Previous mathematical studies demonstrated the potential for achieving a mosquito population equilibrium below the threshold required for sustained malaria transmission when $R_0 < 1$ under a constant ITN usage rate (Agusto et al., 2013; Ngonghala et al., 2014; Laxmi et al., 2022; Ngonghala, 2022). However, these studies often assume a constant rate of ITN use, neglecting significant heterogeneity in real-world ITN usage (Killeen and Smith, 2007; Killeen et al., 2007; Gu and Novak, 2009; Govella et al., 2010; Agusto et al., 2013; Briët et al., 2013; Okumu et al., 2013). This simplification overlooks the intricate processes that influence ITN utilization, including risk perception, which can impact malaria transmission dynamics.

Human behavior significantly influences disease dynamics, either facilitating control efforts through awareness or hindering them, such as when vaccine hesitancy exacerbates the spread of infectious diseases (Agusto et al., 2015; Madhumathi et al., 2021). Using an ordinary differential equations (ODE) framework, the persistence of Ebola in West Africa was attributable to communities' behavior (Agusto et al., 2015). Similarly, we hypothesize that incorporating a proxy quantifying community behavior into an ODE framework will provide insights into malaria progression and provide a better overview of the effectiveness of ITNs.

This study, conducted in James Town and Korle-Dudor, two malaria hotspot areas in Accra, Ghana, offers empirical insights into behaviors affecting malaria control. Using collected data, we employ an epidemiological model that integrates brief community movements (*Lagrangian* movement) into an extended Susceptible Infected Recovered Susceptible - Susceptible Infected (SIRS-SI) model for a more comprehensive analysis. The model assesses urban malaria dynamics, focusing on changes in the basic reproductive number. Our approach combines empirical data and modeling to understand the impact of community behavior on malaria progression, emphasizing scenarios related to ITN use and physical and chemical degradation of ITNs.

2 Materials and methods

2.1 Study area

Accra is in the Greater Accra Metropolitan Area (GAMA), which stretches between 5° 28 'N to 5° 52'N and 0° 32'W to 0° 02'E in Ghana. It is one of the fastest-growing cities in Western Africa, with an annual population growth rate of 3.1% (GSS, 2013). GAMA is a densely populated area with 1,236 people per km². Accra is the main administrative and economic center of Ghana, with a contribution of 69.7% private informal workforce employment, 15% private formal, 12.8% public, and 2.2% of the workforce employed in 2008 (GSS, 2008).

Rapid urbanization in Accra has contributed to the increase in housing cost and a affordable accommodation, resulting in 15% of the population of the city residing in informal settlements, such as inadequately managed neighborhoods and slums (UN-Habitat Ghana, 2009). Accra grapples with a significant malaria burden driven by the fast-growing population density in under-resourced communities. Malaria mortality and morbidity remain high in under-resourced communities such as Korle-Dudor and James Town (Fobil et al., 2012; Austin, 2015), which were selected for this study due to their high malaria prevalence, poor housing infrastructure.

James Town is a poorly managed area, designated by the Accra Metropolitan Assembly as a slum (Tutu et al., 2017). Accounting for an average of 8.5 occupants per room, this community is facing, among others, serious problems with sanitation (Awuah et al., 2014; Tutu et al., 2017). Korle-Dudor exhibits some characteristics of a slum, such as self-made drains and the lack of tarred roads (Awuah et al., 2018). Migrants from all parts of Ghana who work mainly in the informal sector dominate the Korle-Dudor community.

2.2 Community survey

We conducted a household survey in James Town and Korle-Dudor, to assess the communities' perceptions of malaria, with a focus on general knowledge of malaria, care-seeking behavior, and risk factors influencing the use of ITNs. Twenty enumeration areas from a total fifty-three in the two communities were randomly selected. Following the random selection of the enumeration areas, the data collection team performed a detailed survey of households in each of the 20 enumeration areas by selecting 1,200 households for a cross-sectional, in-depth interview. Of the selected households, we obtained a response rate of 85.67%, representing 1,028 households that participated in the survey. Within each household, we applied the Kish criteria (Kish, 1949), considering that any resident of a given household between 18 and 82 years old and who spent at least the last six months had good knowledge of the disease situation. Therefore, regardless of gender, any member of the household older than 17 years with these qualifications had the opportunity to participate in the study on behalf of the household.

2.3 Statistical analysis

To assess general malaria knowledge and related health-seeking behaviors, descriptive statistics were used. Two generalized linear models were run to investigate: i) the relationship between ITN ownership and use, and ii) the factors influencing ITN use. ITN ownership was defined as the proportion of households possessing at least one ITN, following global ITN ownership indicators (Koenker and Kilian, 2014). A regression analysis was performed to investigate the relationship between ITN use and ownership by regressing the number of households using ITNs against those possessing ITNs. Within a simple Poisson regression framework, 1,000 Monte Carlo permutations were used to estimate probability. To estimate parameters and address overdispersion around the mean, robust standard errors were used (Cameron and Trivedi, 2009). The chi-square test was used to validate the model's goodness of fit. Logistic regression was similarly used to elucidate the factors that influence ITN use.

2.4 Mathematical model formulation and assumptions

We developed a SIRS-SI model to capture the dynamics of malaria across multiple patches or dwellings (Bichara and Iggidr, 2018; Chen et al., 2020) and age groups, though our presented results are on two patches and two age groups. The choice of this model is the result of non-formal observation of group heterogeneity (higher malaria in children) and spatial heterogeneity (existing hotspots). Even though we only investigated under-resourced communities, we included patches representing more developed urban areas to decipher the progression of urban malaria. By progression of urban malaria we refer to the changes in malaria prevalence over time. The susceptible-infected-recovered-susceptible (SIRS) component describes the dynamics of malaria within the human population located in each patch, while the susceptible-infected (SI) component models the mosquitoes. For the sake of simplicity, we will continue to refer to *Anopheles gambiae*, which is commonly recognized as the main competent vector of malaria in West Africa (Villena et al., 2022).

The population of humans and mosquitoes is allocated to v patches. Furthermore, the human population has u age groups. The framework accounted for spatial and group heterogeneity (Bichara and Iggidr, 2018). We assumed that the risk of getting infected depends on the location with higher exposure in under-resourced communities (Fobil et al., 2012).

The fraction of human population m_{kji} who travel for a short period of time from patch j to patch k for each age group i is assumed. Each individual belongs to a home patch with a specific risk of infection determined by environmental conditions (Bichara and Iggidr, 2018). This mobility pattern aligns with *Lagrangian movement*, where origins and destinations always remain intact (Gueron et al., 1996). At time *t*, the human population in a specific age group j ($j=1,…,u$) is structured into susceptible (S_j^H), infected

(I_j^H), and recovered with partial immunity (R_j^H) while the population of mosquitoes is divided into susceptible (S_j^v) and infected (I_j^v).

Our model assumes that i) no incubation period before potential transmission, ii) a short lifespan of mosquitoes preventing recovery before death, iii) mosquitoes are confined to their patches (Verdonschot and Besse-Lototskaya, 2014), and iv) humans spending most of their daily time in their home patches, $(j=1,\ldots,v)$.

The total population of humans in patch j is N_j^H and the total *Anopheles gambiae* (the main malaria vector species in Accra, Ghana) population in the same patch is N_j^v. The total human population N_j^H in an isolated patch j (no movement between neighboring patch) at time t is

$$N_j^H = S_j^H + I_j^H + R_j^H$$

Similarly, the total population of mosquitoes N_j^V at this same time t regardless of the connectivity of the human network is

$$N_j^V = S_j^V + I_j^V$$

For group i, β_i is the risk of malaria infection, γ_i is the recovery rate of the infectious individuals, $\wedge_i^H$ is the recruitment rate of the susceptible human population, μ_i^H is the natural mortality rate, and σ_i be the rate immunity is lost. The remaining parameters of the model are described in Table 1 and the interactions between humans and mosquitoes are represented in the flow diagram (Figure 1).

The density within patch j and age group i is defined by the following system of non-linear ordinary differential equations:

$$
\begin{cases}
\frac{dS_{ji}^H}{dt} = \Lambda_{ji}^H \cdot 1_{i=1} + \theta_{j,i-1\to i+1}S_{j,i-1}^H - \theta_{j,i\to i+1}S_{j,i-1}^H - \sum_k \left(\frac{\beta_j^V(1-\zeta\psi_{ji})a_j m_{jki}I_j^V}{N_j^H}\right)S_{ji}^H + \sigma_{ji}^H R_{ji}^H - \mu_{ji}^H S_{ji}^H \\
\frac{dI_{ji}^H}{dt} = \sum_k \left(\frac{\beta_j^V(1-\zeta\psi_{ji})a_j m_{jki}I_j^V}{N_j^H}\right)S_{ji}^H + \theta_{j,i-1\to i}I_{j,i-1}^H - \theta_{j,i\to i+1}I_{j,i-1}^H - (\gamma_{ji}^H + \mu_{ji}^H + \delta_{ji}^H)I_{ji}^H \\
\frac{dR_{ji}^H}{dt} = \gamma_{ji}^H I_{ji}^H + \theta_{j,i-1\to i}R_{j,i-1}^H - \theta_{j,i\to i+1}R_{j,i-1}^H - (\mu_{ji}^H + \sigma_{ji}^H)R_{ji}^H \\
\frac{dS_j^V}{dt} = \Lambda_j^V - \mu_j^V S_j^V - \frac{(\Sigma_k\Sigma_i\beta_j^H m_{jki}I_{ji}^H)}{N_j^H}a_j(1 - \zeta\sum_i^u \frac{\psi_{ki}}{u})S_j^V \\
\frac{dI_j^V}{dt} = \frac{(\Sigma_k\Sigma_i\beta_j^H m_{jki}I_{ji}^H)}{N_j^H}a_j(1 - \zeta\sum_i^u \frac{\psi_{ki}}{u})S_j^V - (\mu_k^V j + a_j\zeta\sum_i^u \frac{\psi_{ki}}{u})I_j^V
\end{cases}
$$
(1)

As there are v patches and u age groups, there are $3vu + 2v$ equations. These equations, with nonnegative initial conditions and fixed mosquitoes and human population, constitute the SIRS-SI epidemic model. The following result shows that the system is well-posed.

Proposition 1: The nonnegative orthant $\mathbb{R}_+^{3vu+2v}$ is positively invariant under the flow of the system (Equation 1) and for all $t > 0$. Furthermore. The solution of the system (Equation 1) is bounded.

2.5 Analysis of the model

Positivity and boundedness of solutions
Lemma 1. The set

$$\Omega = \left\{\left(S_j^H, I_j^H, R_j^H, S_j^V, I_j^V\right) \in \mathbb{R}_+^{3vu+2v} \mid S_j^H + I_j^H + R_j^H \le N_j^H, \quad S_j^V + I_j^V \le N_j^V\right\}$$

is compact and positively invariant for the system (Equation 1).

Proof: Adding the first three equations of the system (Equation 1), representing the compartment of the human population, and the two last equations, which represent the population of mosquitoes, we have the following:

$$\frac{dN_{ji}^H}{dt} = \Lambda_{ji}^H \cdot 1_{i=1} + \theta_{j,i-1\to i}N_{j,i-1}^H - \mu_{ji}^H N_{ji}^H - \delta_{ji}^H I_{ji}^H - \theta_{j,i\to i+1}N_{j,i}^H$$

$$\frac{dN_j^V}{dt} = \Lambda_j^V - \mu_j^V N_j^V$$

Using the comparison theorem (Lakshmikantham et al., 1989), the region Ω is a positively invariant set $\left(\mathbb{R}_+^{3vu+2v}, \left\{S_j^H + I_j^H + R_j^H \le N_j^H\right\}, \left\{S_j^V + I_j^V \le N_j^V\right\}\right)$ is positively invariant; Ω is a compact set.

Disease-free equilibrium

Lemma 2. The disease-free equilibrium (DFE) of the system (Equation 1) is given by $(S_j^{H\star}, 0, 0, S_j^{V\star}, 0)$ where $S_j^{H\star} \ge 0$ and $S_j^{V\star} \ge 0$ where $S_j^{H\star} = [S_{11}^H, S_{12}^H, \ldots, S_{vu}^H]^T$, $S_j^{V\star} = [S_1^V, S_2^V, \ldots, S_v^V]^T$ and 0s represent the vectors of infected and recovered humans and infected mosquitoes.

Remark 2.1: In the absence of human mobility, the system (Equation 1) can be assimilated into a single patch. If human communities live in perfect isolation, that is, there is no movement of susceptible or infected individuals between patches, the disease does not spread between patches, since the residence time matrices are null (Bichara and Iggidr, 2018).

To study the basic reproductive number, it is sufficient to consider only the infected compartments (Diekmann et al., 1990). Thus, the essential components of Equation 1 to assess the basic reproductive number are

$$
\begin{cases}
\frac{dI_{ji}^H}{dt} = \sum_k \left(\frac{\beta_j^V(1-\zeta\psi_{ji})a_j m_{jki}I_j^V}{N_j^H}\right)S_{ji}^H + \theta_{j,i-1\to i}I_{j,i-1}^H - \theta_{j,i\to i+1}I_{j,i-1}^H - \left(\gamma_{ji}^H + \mu_{ji}^H + \delta_{ji}^H\right)I_{ji}^H \\
\frac{dI_j^V}{dt} = \frac{(\Sigma_j\Sigma_i\beta_j^H m_{jki}I_{ji}^H)}{N_j^H}a_j(1 - \zeta\sum_i^u \frac{\psi_{ki}}{u})S_j^V - (\mu_k^V + a_k\zeta\sum_i^u \frac{\psi_{ki}}{u})I_j^V
\end{cases}
$$
(2)

For the rest of the paper, we will consider the *Lagrangian* approach used for the two-patch and two-age group metapopulation model.

Then the system (Equation 2) is re-written as for patch $j \ne k$

$$
\begin{cases}
\frac{dI_{11}^H}{dt} = \left(\frac{\beta_1^V(1-\zeta\psi_{11}^H)a_1 m_{111}I_1^V}{N_1^H} + \frac{\beta_2^V(1-\zeta\psi_{12}^H)a_2 m_{121}I_2^V}{N_2^H}\right)S_{11}^H - (\gamma_{11}^H + \mu_{11}^H + \delta_{11}^H)I_{11}^H - \theta_{11\to 12}I_{11}^H \\
\frac{dI_{12}^H}{dt} = \left(\frac{\beta_1^V(1-\zeta\psi_{12}^H)a_1 m_{112}I_1^V}{N_1^H} + \frac{\beta_2^V(1-\zeta\psi_{22}^H)a_2 m_{122}I_2^V}{N_2^H}\right)S_{12}^H + \theta_{11\to 12}I_{11}^H - (\gamma_{12}^H + \mu_{12}^H + \delta_{12}^H)I_{12}^H \\
\frac{dI_{21}^H}{dt} = \left(\frac{\beta_1^V(1-\zeta\psi_{21}^H)a_1 m_{211}I_1^V}{N_1^H} + \frac{\beta_2^V(1-\zeta\psi_{21}^H)a_2 m_{221}I_2^V}{N_2^H}\right)S_{21}^H - (\gamma_{21}^H + \mu_{21}^H + \delta_{21}^H)I_{21}^H - \theta_{21\to 22}I_{21}^H \\
\frac{dI_{22}^H}{dt} = \left(\frac{\beta_1^V(1-\zeta\psi_{21}^H)a_1 m_{212}I_1^V}{N_1^H} + \frac{\beta_2^V(1-\zeta\psi_{22}^H)a_2 m_{222}I_2^V}{N_2^H}\right)S_{22}^H + \theta_{21\to 22}I_{21}^H - (\gamma_{22}^H + \mu_{22}^H + \delta_{22}^H)I_{22}^H \\
\frac{dI_1^V}{dt} = \frac{\beta_{11}^H m_{111}I_{11}^H + \beta_{12}^H m_{112}I_{12}^H + \beta_{21}^H m_{211}I_{21}^H + \beta_{22}^H m_{212}I_{22}^H}{N_1^H}a_1\left(1 - \frac{\zeta(\psi_{11}+\psi_{12})}{2}\right)S_1^V - (\mu_1^V + a_1\frac{\zeta(\psi_{11}+\psi_{12})}{2})I_1^V \\
\frac{dI_2^V}{dt} = \frac{\beta_{21}^H m_{221}I_{21}^H + \beta_{22}^H m_{222}I_{22}^H + \beta_{11}^H m_{121}I_{11}^H + \beta_{12}^H m_{122}I_{12}^H}{N_2^H}a_2\left(1 - \frac{\zeta(\psi_{21}+\psi_{22})}{2}\right)S_2^V - (\mu_2^V + a_2\frac{\zeta(\psi_{21}+\psi_{22})}{2})I_2^V
\end{cases}
$$
(3)

Where $N_1^H = m_{111}N_{11} + m_{112}N_{12} + m_{211}N_{21} + m_{212}N_{22}$ and $N_2^H = m_{121}N_{11} + m_{122}N_{12} + m_{221}N_{21} + m_{222}N_{22}$. In steady state, the infectious components of the disease-free equilibrium (DFE) of the model is given by $\varepsilon_0 = (S_{11}^H, 0, 0, S_{12}^H, 0, 0, S_{21}^H, 0, 0, S_{22}^H, 0, 0, S_1^V, 0, S_2^V, 0)$ (Lemma 2).

TABLE 1 Description and values of the range of parameters of the malaria model Equation 1.

| Parameters	Description	More developed urban areas	Under-resourced urban areas	Unit	References
Λ_i^H	Recruitment rate of group i	0.000001-5.369485e-05	0.000001-6.438356e-05	day^{-1}	(GSS, 2013; Awine and Silal, 2020)
β_i^H	Transmission rate from infected human group i	0.08	0.08	–	(Smith et al., 2012)
μ_i^H	Natural death rate of the humans in group i	1/(63.48*365)	23.5/(1000*365)	day^{-1}	(GSS, 2013; Awine and Silal, 2020)
δ_i^H	Malaria-induced death rate of humans in group i	2e-05	2e-05	day^{-1}	(Forouzannia and Gumel, 2014; Awine and Silal, 2020)
σ_i^H	Waning immunity rate of the humans in group i	5.5/52	5.5/52	–	(Awine and Silal, 2020)
γ_i^H	Recovery rate of humans in group i	2.2e-03	2.2e-03	day^{-1}	(Nakul et al., 2006)
m_{jki}	Fraction of the human population who travel from patch j path k	0.001-0.3	0.001-0.3	day^{-1}	Estimated
ψ_i^H	ITN use rate of humans in group i for a short period of time	0.3-0.6	0.3-0.6	–	Estimated
Λ^V	Mosquito recruitment rate	300/365	500/365	day^{-1}	Estimated
μ^V	Mortality rate of mosquitoes	0.01	0.01	day^{-1}	Estimated
ζ	Efficacy of ITNs	0.398	0.398	–	(Awine and Silal, 2020)
a	Biting rate of mosquitoes	0.4	0.4	day^{-1}	(Forouzannia and Gumel, 2014)
$\theta_{i'j\rightarrow ij}$	Transition rate from age group i' from the patch j to the group i in the same patch	1/(15*365)	1/(15*365)	–	(Forouzannia and Gumel, 2014)
β^V	Transmission rate from infected mosquitoes	0.11	0.11	–	(Chitnis et al., 2009)
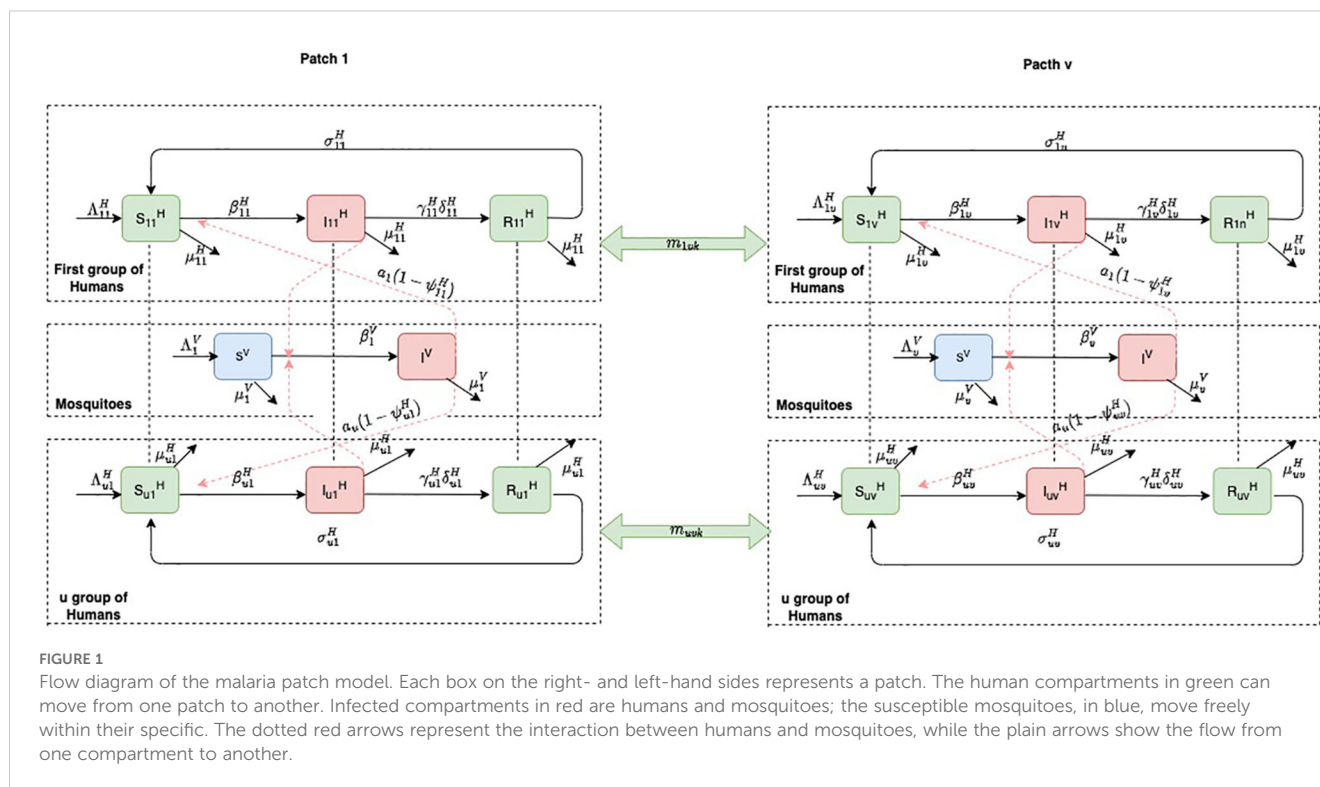
FIGURE 1
Flow diagram of the malaria patch model. Each box on the right- and left-hand sides represents a patch. The human compartments in green can move from one patch to another. Infected compartments in red are humans and mosquitoes; the susceptible mosquitoes, in blue, move freely within their specific. The dotted red arrows represent the interaction between humans and mosquitoes, while the plain arrows show the flow from one compartment to another.

Using the next-generation method (van den Driessche, 2017) we calculate the reproductive number, R_0, which is given by:

$$R_0 = \sqrt{\max(E_l)}$$

where E_l represents the $l = 3vu + 2v = 16$ eigenvalues of the K. The detailed analytical solution of R_0 is given in the Supplemental Material.

2.6 Numerical simulations and scenarios

This model was parameterized using a combination of parameters from previous publications, the Ghana population census (2013), and our community survey (Table 1). The community survey was particularly instrumental in estimating the following parameters, namely the fraction of the population who travel between patches, the maximum value of ITN use in each patch, and the mosquito biting rate in under-resourced areas (where environmental conditions and vector control measures differ significantly from other urban settings, which we then extrapolated to more developed urban areas to account for potential variations in transmission dynamics due to differences in infrastructure and living conditions). The model involves two age groups (children and adults) and two patches (under-resourced- and more-developed urban areas). Four scenarios were tested on the uptake of ITNs (ψ^H) in urban areas. Specifically, we denoted ψ_1^H the rate of ITN use in the more developed urban areas, and ψ_2^H for the rate in the under-resourced areas:

i. The baseline scenario, where ITN use reaches 60% in both under-resource and more developed urban areas with only the human connectivity network (m) varying.

ii. The use of ITNs is assimilated to a coverage rate where the ITN uptake (ψ_i^H) is constant in both patches. Specifically, the use of ITNs in under-resourced neighborhoods is estimated to be lower than in their more developed urban areas counterparts ($\psi_1^H > \psi_2^H$).

iii. The use of ITNs depends on the ownership rate. We assumed that there is a linear relationship between the ownership and use of ITNs where the adoption rate (slope of this linear association) is higher in more developed urban areas.

iv. The use of ITNs varies according to the physical or chemical integrity of the nets. We expressed this use rate by an exponential decay function given by $f(\psi_j^H) = \psi_j^H e^{-\lambda_j t}$ where the decay rate expressed by λ_j is higher in the under-resourced neighborhood.

The scenarios were directly informed by our statistical analysis of the survey data. Specifically, we observed a weak correlation between ITN ownership and actual use, which we interpreted as a potential misrepresentation in policy that high coverage implies high usage. This insight motivated scenaios i) and ii), which test this assumption by modeling ITN use as either equivalent across areas or lower in under-resourced areas, regardless of ownership scenario iii) incorporates the ownership-use relationship identified in the data, with a linear approximation reflecting

greater adoption in better-resourced areas. Scenario iv) was developed based on qualitative findings and reported community behavior indicating that ITN use declines over time between ITN distribution's campaigns, often due to degradation in physical and chemical integrity of the nets; this was implemented via an exponential decay. This approach acknowledges that ITN ownership does not always translate into use, as evidenced by national survey data, and accounts for behavioral and contextual factors influencing utilization (Breakthrough ACTION and VectorWorks). As part of our analysis of community mobility patterns for each scenario, we considered three connectivity networks between under-resourced- and more-developed urban neighborhoods:

1. nearly isolated communities defined by restricted movement ($m_{ikj} = 0.001$);

2. high and homogeneous connectivity between communities up to 30% of each community travel each day and stay in the neighboring community before returning to their home community; and

3. heterogeneous connectivity network where the mobility of the community is age and community-dependent ($m_{ikj} = [0.1 - 0.3]$).

2.7 Global uncertainty and sensitivity analyses

A sensitivity analysis was performed, using Latin hypercube sampling (LHS) and partial rank correlation coefficient (PRCC) to assess the critical inputs (parameters and initial conditions) of the model and quantify how uncertainty affects the basic reproductive number (Marino et al., 2008). For the LHS, we partitioned the distribution of the parameters into 100 equiprobable subintervals. Prior to the PRCC, we determined a monotonic relationship between each parameter and the R_0.

3 Results

3.1 Empirical evidence of malaria risk

Malaria poses a significant health threat in two surveyed communities, where it is perceived as the primary health risk compared to other diseases (Figure 2A). In James Town, 35% of households identify malaria as their primary health concern, while 25.3% of households in Korle Dudor share this perception.

Residents in James Town and Korle-Dudor rely predominantly on repellent coils for malaria prevention, followed by ITNs and other alternatives (Figure 2B). In James Town, 18% of households use repellent coils as their preferred malaria prevention method, while in Korle Dudor, this figure rises to 24%. The prevalent use of ITNs implies a community awareness of their effectiveness, suggesting access to relevant health information. We found that ITN ownership does not statistically explain its use (residual deviance = 17.75675; df = 18 and p-value = 0.472, Table 2). This underscores the influence of other determinants on ITN use within communities.

Logistic regression analysis identifies a statistically significant variable: "Health check week prior to the survey" referring to participants visited a hospital for their own medical needs. (Table 3). A unit increase in the number of times households checked their health status in the week before the survey increased the odds of using ITN by a factor of 1.53. Despite the ownership of ITNs, less than 40% of participants who live in a household that owns at least 1 ITN use them regularly. The key reasons for ITN non-usage include heat generation, limited space, itchiness,

FIGURE 2
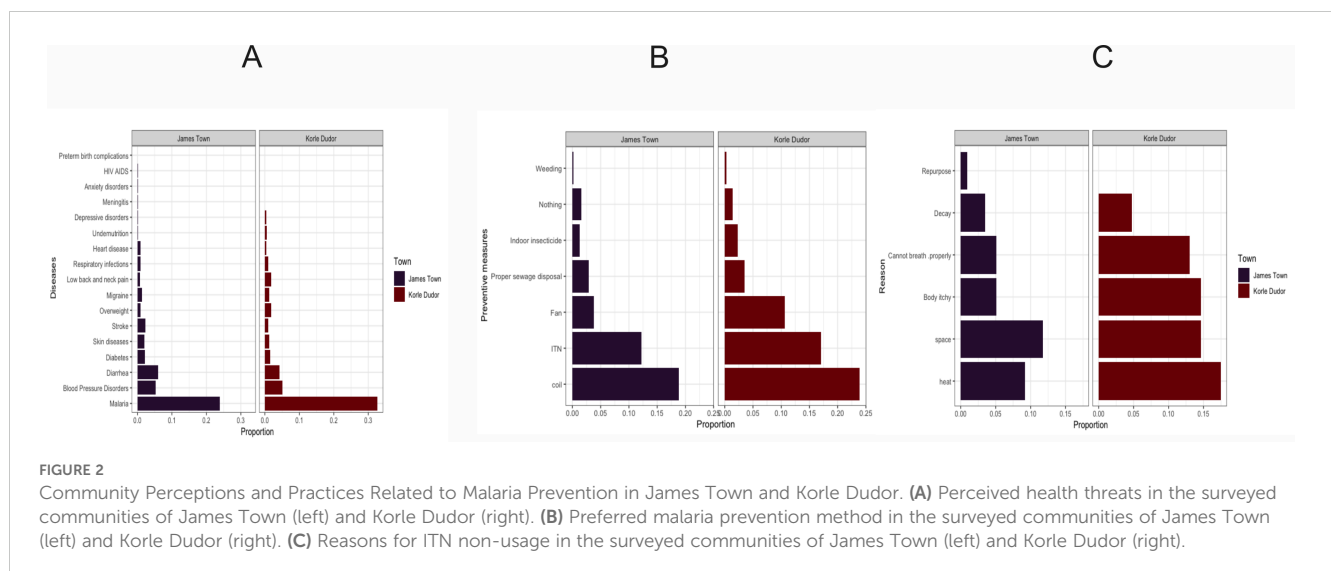Community Perceptions and Practices Related to Malaria Prevention in James Town and Korle Dudor. (A) Perceived health threats in the surveyed communities of James Town (left) and Korle Dudor (right). (B) Preferred malaria prevention method in the surveyed communities of James Town (left) and Korle Dudor (right). (C) Reasons for ITN non-usage in the surveyed communities of James Town (left) and Korle Dudor (right).

TABLE 2   Relationship between ITN ownership and use in two communities of Accra, Ghana.

Predictor variable	Estimate	Robust SE	Pr(>|z|)	LL*	UL*
(Intercept)	13.074	1.216	0.913	8.907	19.190
Ownership of ITNs	1.012	1.005	0.075	1.001	1.023

*LL, lower limit; UL, upper limit; ITN, insecticide-treated bednet.

TABLE 3   Determinants of the Use of ITNs*.

Regressors	Estimate	Std. Error	z-value	Pr(>|z|)	LL	UL
(Intercept)	0.576	0.120	-4.586	4.52E-06	0.455	0.729
Proximity to stagnant water	0.997	0.002	-1.581	0.1139	0.994	1.001
Per capita prevalence	1.218	0.126	1.563	0.118	0.951	1.564
Immediate care-seeking	1.296	0.146	1.78	0.0751	0.974	1.726
Health check the week before the survey	1.530	0.178	2.383	0.0172	1.078	2.171

Insecticide-treated bednets, Per capita prevalence: prevalence estimated at the household level; Immediate care-seeking: refers to the prompt action of individuals seeking medical care or treatment as soon as they recognize malaria symptoms; Health check the week before the survey: refers to participants visited a hospital for their own medical needs.

breathing difficulties, perceived loss of physical/chemical integrity, and repurposing (protecting seedlings, gardening purposes, and fishing) (Figure 2C).

3.2 Scenario analysis of the progression of urban malaria

We used our mathematical model to test several scenarios aiming to get insight into the dynamics that better approximate the current urban malaria progression. In the first scenario, we examined whether 60% ITN coverage is sufficient to reduce the basic reproductive number (R_0). This scenario and the subsequent ones encompass three distinct cases: first, the fraction of human population who move between communities (m) is close to zero, i.e., nearly isolated communities; second, the communities exhibit an equal rate of movement from their origin to the destination; and third, one community travels more than the other.

The second scenario explored different rates of ITN coverage to gauge their impact on urban malaria. The third scenario evaluated different thresholds of ITN use, providing insights into the relationship between coverage and use of ITNs and how this relationship impacts R_0. In the fourth and final scenario, we examined the impact of the decay rate of ITNs on disease dynamics. This assessment approximated community behavior based on the increase in reluctance rate as the ITNs lost their physical or chemical integrity, quantified by the decay rate.

Our results showed that when there is limited movement between communities, R_0 is low, suggesting that the epidemic will likely die out regardless of ITN use except in the case of decay of physical or chemical integrity of the insecticide bed-net, where R_0 reaches 1.59 (Table 4). Moreover, when the coverage of ITNs reaches 60% (baseline scenario), R_0 remains low regardless of the

mobility pattern displayed by the two communities only in the case of nearly isolated communities ($R_0 = 0.57$) (Table 4).

In the second scenario, we found that the disease persists, as $R_o > 1$, when the rate of ITN use is 60% and 30% in well- and under-resourced-urbanized neighborhoods, respectively. This implies that the spatial heterogeneity in ITN use affects the R_0 and subsequently induces persistence in malaria prevalence. For homogeneous and heterogeneous movement, R_0 increases significantly to 22.39 and 30.11, respectively (Table 4). When the use of ITNs is modeled as a linear relationship between use and ownership (in the context of simple linear regression $ITN\ use = ratio\ of\ use \times ownership + intercept$), the disease persists when communities are not isolated ($R_o > 1$). In this case, R_o is higher than in the previous scenario in which ITN use is assimilated into its coverage rate. We observe R_0 values of 0.96 for isolated communities, 28.82 for homogeneous movement, and 38.80 for heterogeneous movement (Table 4).

The fourth scenario revealed that when the decay rate of ITNs is incorporated into the model as a proxy to quantify the decision-making of communities (human behavior), the basic reproductive number is even higher. Specifically, R_0 reaches 1.59 under isolation, 47.71 with homogeneous movement, and up to 60.53 under heterogeneous movement, indicating a major potential for an outbreak in urban settings despite average ITN coverage of 60% (Table 4).

3.3 Sensitivity analysis

Based on the results of Latin hypercube sampling (LHS) combined with the partial rank correlation coefficient (PRCC) conducted on the model parameters using R_o as the output metric, we conclude that the transition rate (θ) is positively

TABLE 4 Basic Reproductive number R_o obtained for each of the scenarios and connectivity network.

Characteristic of the connectivity networks	i) Homogeneous use of ITNs Baseline (60%)	ii) Constant rate per community (60-30)	iii) Heterogenous use of the ITN-based ratio per community (ITN coverage 60 and the slope 70-30)	iv) Heterogeneous use-based decay of ITNs (ITN coverage 60 and decay 1.62-2.5)
1) Nearly isolated communities m=0.01	0.57	0.75	0.96	1.59
2) Homogenous movement of population m=0.3	17.03	22.39	28.82	47.71
3) Heterogeneous movement of population m ∈[0.1-0.6]	19.47	30.11	38.80	60.53

related to the increase in malaria infectivity regardless of the mobility pattern or spatial heterogeneity of ITN use by communities and appears to have more significant impact on R_o than other parameters (Supplementary Figure S1).

4 Discussion

During the last two decades, significant progress has been made in reducing malaria deaths in endemic areas through pharmaceutical (e.g., ACT-based co-therapy) and nonpharmaceutical control measures. While ITNs have proven effective in reducing malaria cases and fatalities in Ghana (Scates et al., 2020), our study reveals that ITN ownership does not always translate to its use.

Our findings challenge two common assumptions: first, that coverage rates can be interpreted as usage rates; and second, that ownership necessarily leads to usage - for example, assuming a proportional relationship such as usage = coefficient × ownership (Lengeler, 2004). Previous models that assumed uniform ITN distribution may have resulted in inaccurate predictions. Notably, our empirical findings are consistent with previous research indicating higher ITN use in low-density households (Abotsi, 2009). Living space was identified as a significant barrier to ITN use in densely populated areas such as James Town and Korle-Dudor (Danso-Wiredu, 2018). Despite their proven efficacy, ITNs face practical challenges in such communities due to space constraints. Because of the immediate pay-offs driven by socioeconomic conditions, repurposing ITNs for agriculture or fishing is common (Laxmi et al., 2022).

Previous studies highlight the complexity of ITN use beyond mere ownership, with discrepancies between possession and actual usage. For example, while 92% of households in one study owned at least one ITN, only 72% reported using them (Kateera et al., 2015). Key factors influencing use include gender (males are 0.4 times less likely to use nets than females), socioeconomic status (lower usage in low-SES households), net availability (reduced use with fewer than two nets), and sleeping arrangements (those sleeping on the floor are less likely to use nets). These findings reinforce the importance of targeted strategies addressing specific barriers to ITN adoption. Similarly, our study underscores the need for localized interventions, as malaria education, particularly after visits to healthcare facilities, significantly increases ITN use, consistent with previous research (Krezanoski et al., 2010; Amoran et al., 2012; Deribew et al., 2012).

Our research shows that in modeled urban areas reaching 60% ITN use without accounting for spatial heterogeneity can eliminate malaria. Incorporating spatial factors, on the other hand, results in persistent malaria, emphasizing the importance of local heterogeneity. In this case, 60% ITN use in each community rather than as an average for the entire urban area is required to eliminate the epidemic. The persistence of urban malaria despite high ITN coverage is explained by heterogeneous spatial patches, a proxy for heterogeneous social behavior.

National-level data from DHS and MIS (Breakthrough ACTION and VectorWorks) suggest that ITN use is often higher

among lower-income groups due to targeted distribution efforts, and that ownership does not always align with wealth status. However, different patterns may emerge at the community level, as demonstrated by our study, which focuses on two specific urban areas where ITN usage does not necessarily correspond with access. This underscores the necessity of incorporating localized behavioral and contextual factors into the adoption of ITNs, as opposed to relying on broad generalizations.

Recognizing the difficulty of modeling human behavior, our proxy-based approach focuses on ITN non-use due to integrity loss. While it does not fully capture human behavior, it does shed light on urban malaria persistence, with ITN coverage exceeding 60%.

Our findings show that heterogeneous ITN use is influenced by spatially diverse human behavior. While communities recognize the benefits of ITNs, they are concerned about net decay. To increase uptake, we recommend shorter ITN distribution intervals combined with regular malaria education and follow-ups (Ngonghala, 2022). Integrating group and spatial heterogeneity into compartmental models improves understanding of urban malaria persistence.

This study notable limitation centered around the reliance on the basic reproductive number (R_o) as a crucial indicator of disease persistence. By exclusively using R_o, we overlooked scenarios involving backward bifurcation, where the disease can persist despite having $R_o < 1$ (Mamo, 2023). However, the utilization of this proxy and scenario-based approach underscored the significance of human behavior. This emphasizes a pivotal realization: the mere distribution of ITNs is insufficient to eradicate malaria. Instead, the focus should extend to community education, encouraging adoption, and promoting strict adherence to ITN use. This nuanced perspective sheds light on the intricate interplay between human behavior and disease dynamics.

Furthermore, we did not investigate the rivalry amongst competent urban malaria vectors in our study for simplicity. A growing body of startling evidence indicates that *An. stephensi*, a versatile species better suited to urban environments, outcompetes *An. gambiae* (Samarasekera, 2022). There is proof that *An. stephensi* can grow in harsh man-made environments, like bottles of water, polluted water, during the dry season (Surendran et al., 2018; Yared et al., 2023). Furthermore, *An. stephensi*'s opportunistic feeding and resting habits is propelling its spread throughout Africa's cities. Although *An. stephensi* is not within the purview of our study, there is evidence that human behavior may contribute to the resurgence or persistence of urban malaria, particularly in the context of our demonstration that the community's movement away from areas of varying exposure risk and the reluctance to use ITNs together account for the most likely explanation of the current progression of urban malaria. Despite the resistance of *An. stephensi* to pyrethroid (Hancock et al., 2020; Moyes et al., 2020), the primary ingredient in ITNs, which serve as a physical barrier that keeps mosquitoes and humans apart, frequent use of ITNs should still contribute to reducing the growing risk of malaria cases in African cities.

Another limitation of our study pertains to the indicator used for measuring ITN ownership. Specifically, this indicator fails to account for the actual usability of the nets owned by households. For instance, consider a household that possesses only one net but is possess of six members. This household would be classified with the same level of ITN ownership as another household that owns three nets but also has six members. Both households meet the basic criterion of owning at least one ITN; however, the practical implications for net usage among the members of each household are different. The household with a single net faces the challenge the distribution of that net among six individuals raising questions about accessibility and equitable use among members. In contrast, the household with three nets has a greater capacity to provide adequate protection for its members, thereby enhancing the likelihood of effective malaria prevention. Thus, the ITN ownership metric alone cannot comprehensively capture the nuances of ITN access and availability within different household contexts. While it is true that the ITN ownership indicator has limitations, it is essential to recognize its value in providing a basic measure of net access within households and providing context to analyze the dynamics of urban malaria.

5 Conclusion

For the programmatic planning of ITN distribution, we strongly recommend incorporating estimates that account for human behavior. Doing so will enhance the accuracy of the model outcomes. Additionally, we propose considering stochasticity in the model estimates to enable more versatile and informed decision-making processes. Furthermore, we advocate for an exploration of the backward bifurcation of the system using a similar model. This approach empowers policymakers to assess the effectiveness of existing non-pharmaceutical measures and gain a more precise understanding of the progression of malaria. Lastly, we emphasize the importance of allocating additional efforts and resources towards community education. This initiative aims to encourage communities to prioritize the use of ITNs and other malaria preventive measures. In the current state, the lack of space for ITNs, the use of other alternative like the use of insect spray, and the coils, especially in less privileged communities act as strong counterarguments inhibiting daily use of ITNs. By fostering greater awareness and adherence for this targeted audience utilizing socio-media for example, we anticipate a substantial reduction in malaria prevalence, potentially paving the way for malaria elimination in sub-Saharan Africa. However, challenges in implementing these recommendations should be acknowledged. The complexity of human behavior, socioeconomic constraints, and the need for consistent community engagement may hinder the widespread adoption of these measures. Addressing these obstacles will require ongoing effort, collaboration, and adaptation to local contexts to ensure the success of malaria control initiatives.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Ethics statement

This study was approved by both the ethics committees of ZEF and the Institute of Statistical, Social, and Economic Research (ISSER), University of Ghana, on 28 September 2018 and 04 February 2020, respectively. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and institutional requirements.

Author contributions

MS: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. LC: Conceptualization, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Writing – review & editing. CB: Funding acquisition, Project administration, Resources, Supervision, Validation, Writing – review & editing, Conceptualization, Investigation, Visualization.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmala.2025.1571912/full#supplementary-material

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