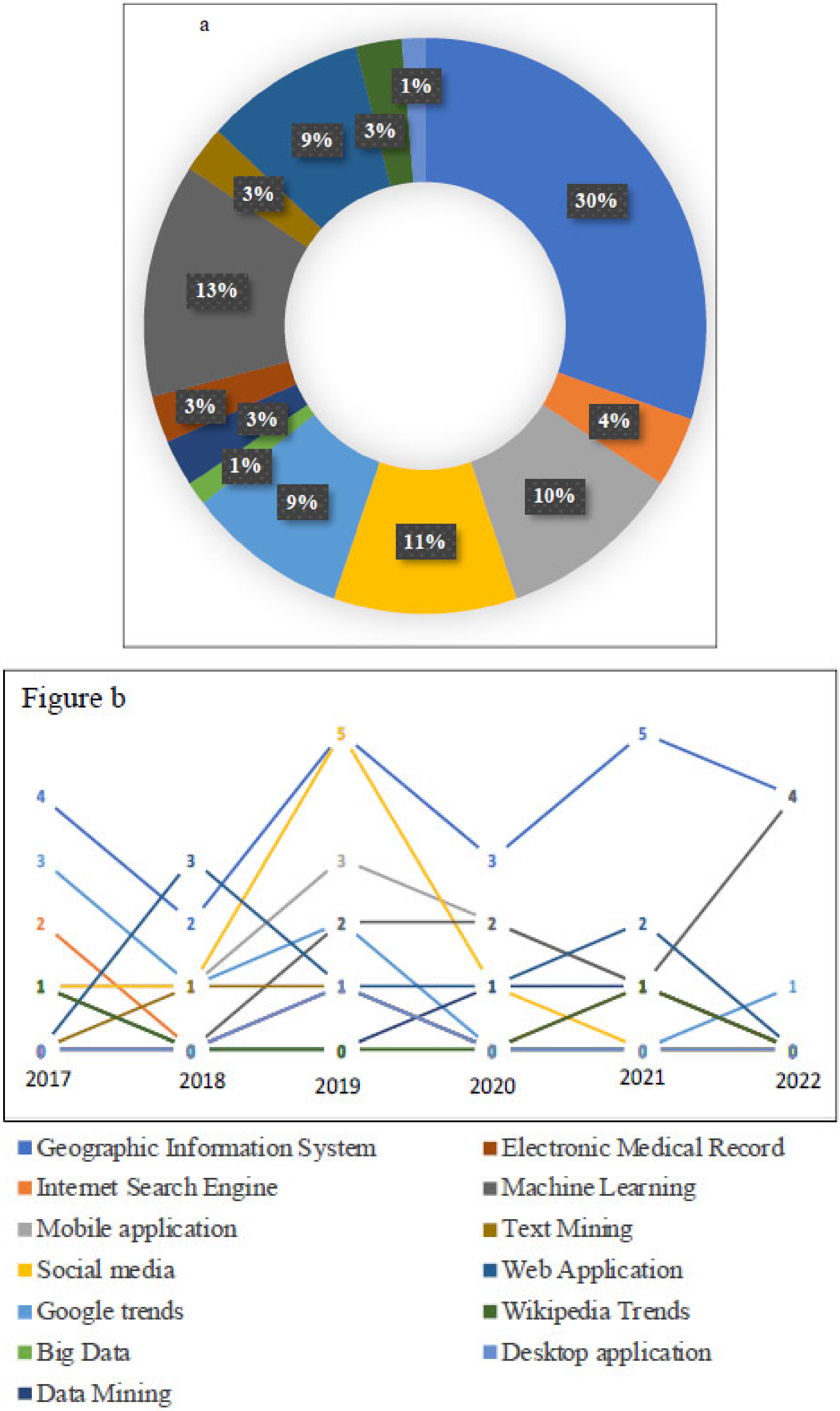

Fig. (3). (**a**) Percentage of digital health categories and trends.
(**b**) Trends of DHIs on dengue surveillance.

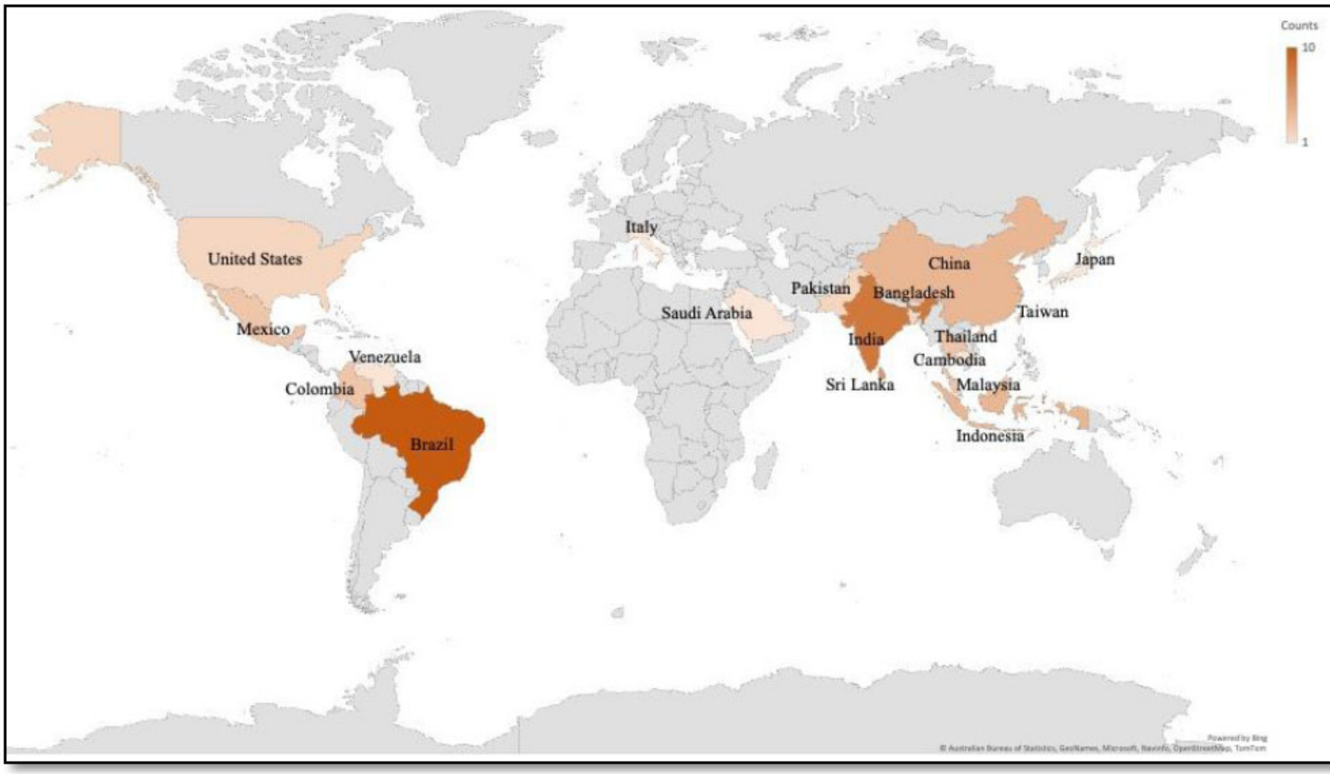

Fig. (4). Geographic distribution of studies.

Technological advances such as DHIs in dengue surveillance have enabled many countries to integrate surveillance data globally. However, international institutions such as the World Health Organization (WHO) must set standards related to policies or regulations, resources, and processes to integrate surveillance data globally. By integrating surveillance data for dengue, including clinical, entomological, microbiological/ serological, epidemiological, meteorological, and environmental information, we can gain a holistic understanding of the dengue situation and effectively predict and respond to epidemics [32–36].

This study found 13 different DHIs categories in Dengue surveillance with annual trends (Fig. **3b**). GIS is consistently used in Dengue fever surveillance every year. However, there is an interesting thing, namely machine learning that has begun to appear in the last 2 years in Dengue surveillance. This possibility is related to the desire of researchers to predict Dengue incidences. With the use of ICT and other technologies, machine learning is becoming a crucial approach in the field of digital health [37, 38].

3.3. Geographical Distribution of Digital Health in Dengue Surveillance Studies

Fig. (**4**) displays the distribution of the article sites that were chosen for a study concerning the use of digital health in Dengue surveillance around the globe. According to the papers analyzed, Brazil (10 articles), India (8 articles), Sri Lanka (6 articles), China (4 articles), and Indonesia (4 articles) are the top 5 countries for using DHIs in Dengue surveillance. The articles are spread out throughout tropical nations, as seen on the map (Fig. **4**). We found that a high number of publications in these countries correlated with a high Dengue prevalence. For example, in Brazil [39, 40], India [41], Sri Lanka [42, 43], China [44, 45], and Indonesia [43] which are also known as Dengue endemic countries.

Additionally, if we look deeper into the DHIs utilized in the top 5 countries, we find that they differ substantially. According to this study, social media (Twitter) is more dominantly discussed (5 articles) in Brazil, while GIS is more dominantly discussed in India (5 articles). Sri Lanka also discusses GIS (2 articles) and Mobile Apps (2 articles). Machine learning (3 articles) and internet search engines (3 articles) dominate in China. Lastly, there is no dominant force in Indonesia; each article discusses GIS, mobile apps, machine learning, and social media (Twitter).

3.4. The Purpose of DHIs in Surveillance Dengue

The purpose of the DHIs in these articles varies greatly depending on the type of DHIs, such as to identify risk areas, predict Dengue cases, develop an early warning model, assist in disease monitoring and surveillance, track Dengue case numbers, and others. Forecasting or predicting the incidence of Dengue is the objective that is most frequently discussed. However, there is an interesting research objective that is not widely discussed, namely the use of Twitter data to measure transmission based on human behaviors and movement. An algorithm is created to generate a dynamic mobility-weighted incidence index using geolocated data from Twitter (MI). According to this study, the MI index can improve timely decision-making within the public health system and is useful and significant for Dengue surveillance and early warning systems [46].

This review found various research designs mentioned in these review articles such as spatial analysis, cross-sectional studies, mixed method studies, design and development studies, big data analytics, data analytics, and ecological studies. The research design that is most widely used in researching DHIs in Dengue surveillance is the spatial analysis and this relates to GIS as the most discussed DHIs category in the previous paragraph. Furthermore, the most frequently used data sources, both conventional and digital, are surveillance data, climate data, internet big data, social media data, sociodemographic data, and remote sensing image data. More detailed information can be seen in Table **2**.

Table 2. Digital health purposes in dengue surveillance.

No.	Study/Refs.	Digital Health Interventions	Data Sources	Types of Studies	Purposes
1	Ashby *et al*. 2017 [47]	Geographic Information System	Surveillance data, population data, remote sensing data	Spatial analysis	To identify risk areas of Dengue fever
2	Guo *et al*. 2017 [48]	Internet Search Engines, Machine learning	Surveillance data, meteorological data, demographic data	Data Analytics	To develop an accurate Dengue prediction model
3	Li *et al*. 2017 [49]	Internet Search Engine	Baidu website, surveillance data, meteorological data, demographic data	Data Analytics	To develop an early warning model by integrating query data from the internet into traditional surveillance data
4	Lwin *et al*. 2017 [50]	Mobile applications	Real-time data from the mobile app	Development study	To digitize form completion and collect site visit information, real-time surveillance of Dengue outbreaks, infographics, and education
5	Marques-Toledo *et al*. 2017 [51]	Social media	Surveillance data, Twitter data, sociodemographic data, big data Google, Wikipedia data	Data Analytics	To evaluate and demonstrate the utility of tweet modelling in Dengue estimate and forecasting
6	Sirisena *et al*. 2017 [22]	Geographic Information System	Meteorological data, surveillance data	Spatial analysis	To map and evaluate the spatial and temporal distribution of Dengue in Sri Lanka from 2009 to 2014, and to investigate the relationship between climatic factors and Dengue incidence
7	Strauss *et al*. 2017 [24]	Google Trends	Big data Google, Surveillance data	Analysis trend/ time series	To compare the accuracy of GDT with traditional surveillance systems in Venezuela
8	Valson *et al*. 2017 [52]	Geographic Information System	Meteorological data	Spatial analysis	To analyze the spatiotemporal clustering of Dengue cases and their climatic and physiological environmental correlations
9	Yang *et al*. 2017 [53]	Google Trends	Big data Google	Data Analytics	To generate near-real-time Dengue case estimations in five countries/states: Mexico, Brazil, Thailand, Singapore, and Taiwan
10	Manogaran *et al*. 2018 [54]	Big data, Geographic Information Systems	Meteorological data	Data Analytics	To propose a big data-based surveillance system that analyses spatial climate big data and performs continuous monitoring of the correlation between climate change and Dengue
11	Ho *et al*. 2018 [55]	Google Trends	Big data Google, Surveillance Data	Data Analytics	To evaluate the health-seeking behavior based on Dengue-related search queries and to assess the temporal association between weekly GDT and Dengue occurrence
12	Hussain-Alkhateeb *et al*. 2018 [56]	Web applications	Meteorological, epidemiological, and entomological indicator	Development study	To detect potential Dengue epidemics and initiate early response activities
13	Rizwan *et al*. 2018 [57]	Web applications, Geographic Information Systems	Surveillance data	Design and development study	To assist in disease monitoring and surveillance
14	Sousa *et al*. 2018 [31]	Web applications, Mobile applications, Geographic Information Systems, Social media	Twitter database	Design and development study	To assist in Dengue monitoring and surveillance

No.	Study/Refs.	Digital Health Interventions	Data Sources	Types of Studies	Purposes
15	Villanes *et al*. 2018 [58]	Text mining	Online news	Text mining	To describe, analyze and predict Dengue cases
16	Babu *et al*. 2019 [59]	Mobile applications, Geographic Information Systems	Surveillance data	Development study	To upload surveillance data, collect key environmental parameter data, collect relevant information from the community, and generate dynamic risk maps.
17	Jain *et al*. 2019 [60]	Machine learning, Geographic Information System	Meteorological data, clinical data, socioeconomic data, and the data encoding spatial	Big Data Analysis	To forecast the occurrence of Dengue fever within a geographical area
18	Lwin *et al*. 2019 [61]	Mobile applications	Surveillance data	Design and development study	To increase the flow of information and improve Dengue surveillance, with the ultimate goal of reducing disease spread
19	Ocampo *et al*. 2019 [62]	Mobile applications, Geographic Information Systems, Web Based Application	Surveillance data	Design and development study	To facilitate the capture and analysis of epidemiological information, mapping, visualization in graphical reports, real-time monitoring, and risk stratification.
20	Zhang *et al*. 2019 [63]	Text mining	Online news	Big Data Analysis	To track Dengue case numbers and provide near real-time reporting on outbreak development
21	Guo *et al*. 2019 [64]	Internet Search Engines, Geographic Information Systems, Machine Learning, Social media	Surveillance data, social media data, climate data,	Development study	To develop an ensemble penalized regression algorithm (EPRA) to begin near-real-time predictions of the Dengue epidemic trajectory
22	Ledien *et al*. 2019 [65]	Desktop application	Surveillance data	Development study	To identify appropriate tools for improving the early warning system and preparation
23	Mizzi 2019 [66]	Google trends, social media	Online data	Data Analytics	To forecast Dengue incidence
24	Ramadona *et al*. 2019 [46]	Social media	Online data	Development study	To design an algorithm to estimate a dynamic mobility-weighted incidence index (MI), which assesses the level of exposure to virus importation in any particular area, to quantify the Dengue virus importation pressure in each study neighborhood monthly
25	Rangarajan *et al*. 2019 [67]	Electronic Medical Records, Google Trends	Medical Records of Patient, online data	Data Analytics	To forecast Dengue incidence
26	Souza *et al*. 2019 [68]	Social media, Geographic Information Systems	Online data	Data Analytics	To create two probability models to characterize high-risk areas
27	Damayanti *et al*. 2020 [69]	Machine learning	Surveillance data	Big Data Analysis	To predict the occurrence of Dengue
28	Faridah *et al*. 2020 [70]	Web applications	Surveillance data	Evaluation study	To provide surveillance data, visualize, report, and support decision making
29	Herbuela *et al*. 2020 [29]	Mobile application, Geographic Information System	Real-time data from the mHealth app	Design and development study	o enhance awareness, improve knowledge, and change attitudes about Dengue fever, health-seeking behavior, and intent-to-change behavior on Dengue fever prevention among users
30	Somboonsak 2020 [71]	Mobile application, Geographic Information System	Patient data from the Bureau of vector-borne diseases	Development study	To create predictions and alert people *via* smartphone
31	Amin *et al*. 2020 [72]	Machine learning, social media	Social media data	Data Analytics	To predict and monitor the epidemic outbreak
32	Khalique *et al*. 2020 [73]	Geographic Information System, data mining	Surveillance data	Data Analytics	To detect significant hotspots over a region to implement sentinel surveillance
33	Faridah *et al*. 2021 [74]	Geographic Information System	Surveillance data	Spatial analysis	To offer strategic information for the Dengue management program, to predict potential Dengue outbreaks, to improve information needed for effective planning, and to investigate the demographic pattern of Dengue cases
34	Gulley *et al*. 2021 [75]	Electronic Medical Record	Medical Record of Patient	Data Analytics	To assess temporal and demographic factors
35	Herbuela *et al*. 2021 [76]	Mobile applications	Respondent	Cross-sectional mixed method study	To provide early detection of disease outbreaks
36	Parikh *et al*. 2021 [77]	Web-based, Geographic Information System, Machine Learning	Database: WHO, PAHO, World Bank, and Gideon	Design and development study	To detect the infectious disease re-emergence (Dengue)
37	Provenzano *et al*. 2021 [78]	Wikipedia Trends	Data from Wikipedia	Cross-sectional study	To assess the temporal relationship between Wikitrends and traditional surveillance data

No.	Study/Refs.	Digital Health Interventions	Data Sources	Types of Studies	Purposes
38	Ramesh *et al*. 2021 [79]	Geographic Information System	Surveillance data	Cross-sectional study	To investigate the correlation between Dengue cases and vector indices
39	Ranwala *et al*. 2021 [80]	Web applications	Surveillance data	Development study	To provide an early warning and response system for Dengue, as well as to supplement existing surveillance
40	Tasnim *et al*. 2021 [81]	Data Mining, Machine Learning	Online news	Data analytics/ Data mining	To uncover useful information and create a Dengue news surveillance system
41	Withanage *et al*. 2021 [82]	Geographic Information System	Data from Survey	Cross-sectional study	To detect risk hotspots of Dengue
42	Lin 2022 [83]	Geographic Information System	Surveillance data	Spatial analysis	To identify the cluster and explore different routes of epidemic propagation
43	Al-Nefaie *et al*. 2022 [84]	Geographic Information System	Surveillance data	Cross-sectional study	To investigate the geographic patterns of Dengue cases to see if there is a correlation between the following environmental factors and Dengue fever
44	Baak-Baak *et al*. 2022 [85]	Machine learning	Surveillance data	Data Analytics	To conduct a spatial and temporal analysis of Dengue cases and deaths in Mexico
45	Carabali *et al*. 2022 [86]	Geographic Information System	Surveillance data	Spatial analysis	To quantify the contribution of the area- and observed case-specific variables while simultaneously analyzing the geographical distribution
46	Chang *et al*. 2022 [87]	Machine learning	Email Database	Data Analytics	To improve the efficiency of monitoring the epidemic situation in Southeast Asia
47	Harsha *et al*. 2022 [88]	Geographic Information System	Surveillance data, census data, satellite image data	Spatial analysis	To identify the Dengue risk areas
48	Koplewitz *et al*. 2022 [89]	Google trends, machine learning	Epidemiological data, weather data, and big data Google	Big Data Analytics	To estimate Dengue incidence
49	Masrani *et al*. 2022 [90]	Geographic Information System	Surveillance data	Spatial analysis	To examine changes in Dengue case trends and spatial patterns
50	Roster *et al*. 2022 [91]	Machine learning	Surveillance data	Data Analytics	To create a model for forecasting monthly Dengue cases in Brazilian cities one month in advance
51	Santana *et al*. 2022 [92]	Geographic Information System	Surveillance data	Ecological Study	To explore the spatiotemporal dynamics of Dengue-related mortality and to identify potentially linked factors.

Based on the objectives of these DHIs for Dengue surveillance system, they are very relevant from the ONE Health perspective, especially for effective dengue prevention and control strategies. The ONE Health perspective recognizes the interconnectedness between human, animal, and environmental health. By integrating a surveillance system into the dengue intervention strategy, information on clinical cases, vector presence, and environmental conditions can be effectively monitored and analyzed to detect and respond to outbreaks in a timely manner. This integrated approach would involve linking clinical care, vector and virus surveillance, and environmental surveillance. This integration would also involve engaging community members and stakeholders from sectors not typically involved in disease control. By integrating surveillance systems into the dengue intervention strategy, we can improve the ability to detect and monitor the spatial and temporal distribution of dengue cases, identify high-risk areas for intervention, and establish alert thresholds for outbreaks [93–95].

3.5. Future Digital Health Interventions on Dengue Surveillance

This study provides several recommendations for future DHI research on Dengue surveillance, specifically regarding topics, objectives, and methodologies. First, we advise that studies on machine learning, big data, data mining, and other fields focus on predicting or forecasting upcoming Dengue outbreaks using a spatiotemporal approach. With a spatiotemporal approach, we will know when and where there is an increase in Dengue cases (outbreaks). This is closely related to the condition of predictors of Dengue events, which always change dynamically, such as environmental conditions, climate, mosquitoes (agents), humans (host), and others. The second point is related to the implementation method, our recommendation is to combine and integrate surveillance data sourced between conventional surveillance and digital surveillance so the accuracy can be relied upon. Finally, researchers can use data available on digital platforms for Dengue surveillance purposes.

Furthermore, we recommend researchers who will conduct research or develop DHIs for Dengue surveillance to leverage vaccination data as a data source. The utilization of vaccination data is an essential dimension of surveillance for Dengue, especially in areas where Dengue vaccines have been introduced. However, based on the studies we reviewed, no articles were found that used vaccine data as a source of DHIs data.

4. LIMITATIONS

This review has certain limitations. First, because of the wide scope of this study, the knowledge gap in DHIs on Dengue surveillance is also not very detailed, *i.e*., there are no specific categories of DHIs. Future study reviews may focus on a narrower scope to identify gaps at a deeper level; for example, the review may simply focus on the topic of machine learning and identify knowledge gaps on this topic. Second, neither the risk of bias nor the quality of the research reviewed were evaluated. So, the topic or theme may have been studied before but we don't have the quality of the study. Therefore, if you wish to research the same topic or theme, we recommend studying past studies carefully and designing their studies on top of previous studies, taking also into account the risk of bias and the quality of previous studies. Finally, this research can be used as a reference in researching and developing DHIs for Dengue surveillance according to the aims and needs of researchers.

CONCLUSION

This review has demonstrated the use of DHIs across tropical countries and the top 5 countries were Brazil, India, Sri Lanka, China, and Indonesia. There were 13 different categories of digital health and GIS dominates the use of digital health in Dengue surveillance followed by Machine Learning, Social Media, Mobile Applications, Google Trends, and Web Applications. A single Dengue surveillance program uses various DHIs simultaneously, indicating that the use of digital health was integrated. Future digital health on Dengue surveillance should explore the synergies across various combinations due to the significant emphasis on integrated health systems and interoperability to decide which packages of digital health are the most effective and efficient. Recommendations for future research should focus on how to leverage vaccination data and integrate all available data sources and methodologies to increase data completeness and predictive model accuracy so that Dengue outbreaks can be detected earlier.

AUTHORS' CONTRIBUTION

Conceptualization: All authors ; Data curation: M.F.S., D.D.N. ; Formal analysis: M.F.S. ; Methodology: All authors ; Visualization: M.F.S. ; Writing–original draft: M.F.S. ; Writing–review & editing: all authors.

LIST OF ABBREVIATIONS

LMICs	=	Low And Middle-income Countries
WHO	=	World Health Organization
DSS	=	Dengue Shock Syndrome

CONSENT FOR PUBLICATION

Not applicable.

STANDARDS OF REPORTING

PRISMA guidelines and methodology were followed.

AVAILABILITY OF DATA AND MATERIALS

The data and supportive information are available within the article.

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

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SUPPLEMENTARY MATERIAL

PRISMA checklist is available as supplementary material on the publisher's website along with the published article.

Supplementary material is available on the publisher's website along with the published article.

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