Research Article

Using Google Trends to Predict Dengue Outbreaks in Pakistan: A Time-Series and Causality Analysis

Alizeh Sonia Fatimi[1], Tazeen Fatima[2], Asghar Nasir[3], Muhammad Shariq Shaikh[4], Imran Siddiqui[5], Sibtain Ahmed[5*]

[1]*Medical College, Aga Khan University, Karachi, Pakistan*
[2]*Pathology and laboratory services, NICVD Karachi*
[3]*Section of Molecular Pathology, Department of Pathology and Laboratory Medicine, Aga Khan University, Karachi, Pakistan*
[4]*Section of Hematology, Department of Pathology and Laboratory Medicine, Aga Khan University, Karachi, Pakistan*
[5]*Section of Chemical Pathology, Department of Pathology and Laboratory Medicine, Aga Khan University, Karachi, Pakistan*

Article Info

[*]***Corresponding Author:***
Sibtain Ahmed
Assistant Professor & Consultant Chemical Pathologist
Department of Pathology and Laboratory Me
Aga Khan University Hospital
Stadium Road Karachi Pakistan
Phone: +92 21-34861951
E-mail: sibtain.ahmed@aku.edu

Abstract

Background: Dengue fever is a significant public health issue in Pakistan. Seasonal outbreaks lead to considerable illness and economic strain. Traditional surveillance systems, like the Integrated Disease Surveillance and Response (IDSR) system, depend mainly on passive reporting. They often identify outbreaks only after transmission has already worsened. Digital data sources, such as Google Trends, might provide early signs of increasing disease activity by reflecting changes in public information-seeking behavior.

Objective: To determine if Google search activity for dengue-related terms can predict dengue case counts in Pakistan during 2024.

Methods: Weekly dengue case count data were collected from the IDSR Weekly Bulletin. Weekly Relative Search Volume (RSV) data for "dengue," "dengue fever," "dengue symptoms," and "dengue treatment" were gathered from Google Trends. Case counts were adjusted to a 0–100 scale. Pearson correlation was used to examine the relationship between search activity and case count data. Time-series causality analysis was carried out using the Toda–Yamamoto method, following tests for stationarity and the specification of the Vector Autoregression (VAR) model.

Results: Strong positive correlations were found between dengue-related search interest and case count data ($r = 0.756–0.832$; $p < 0.001$). The strongest correlation was for the term "dengue." Toda–Yamamoto causality testing showed that search activity significantly predicted subsequent increases in dengue case counts for "dengue symptoms" ($p = 0.004$), "dengue treatment" ($p = 0.001$), and "dengue" ($p = 0.004$), with an approximate two-week lag.

Conclusion: Google Trends search data effectively reflects and can anticipate dengue case count patterns in Pakistan. This suggests that it could serve as a cost-effective, real-time early warning tool to complement the national surveillance system. Combining digital search monitoring with IDSR reporting could lead to earlier detection and a more proactive public health response.

Introduction

Dengue fever is one of the most common mosquito-borne infections in Pakistan. It causes thousands of cases each year and continues to challenge the country's public health system [1]. The Dengue virus (DENV), a member of the Flavivirus genus, has four antigenically distinct serotypes (DENV-1–4) spreads through Aedes aegypti and Aedes albopictus mosquitoes, which breed in stagnant water during and after the monsoon season [2]. Seasonal dengue outbreaks happen almost every year, with major peaks usually occurring between September and November. Most cases come from the Punjab and Sindh provinces, especially in large urban centers like Karachi, Lahore, and Rawalpindi [3]. According to national surveillance data, more than 28,427 confirmed cases and multiple fatalities were reported in 2024 [4]. This made it one of Pakistan's more severe outbreaks in recent years.

Several factors contribute to the increasing frequency and intensity of dengue outbreaks in the country. These factors include unplanned urban growth, inadequate drainage, and sanitation systems, and shifting rainfall patterns due to climate change [3]. A study conducted in four major Pakistani cities estimated the average direct cost per dengue patient to be Rs. 35,823 (approximately US $358 at the time of the study), highlighting the substantial economic burden associated with the disease. This cost reflects hospital admissions, diagnostic testing, vector control measures, and loss of productivity [5]. Even though dengue outbreaks are predictable, early warning systems are still weak. Outbreaks are frequently noticed only after hospitals report a rise in patients [6].

The Integrated Disease Surveillance and Response (IDSR) system is Pakistan's main framework for tracking and reporting dengue cases. It gathers weekly outbreak reports from both public and private healthcare facilities. However, the system mainly uses passive surveillance [7]. This approach can cause delays in reporting and lead to an undercount of actual cases. Many areas also have limited laboratory confirmation, making it hard to produce timely and accurate outbreak alerts. Furthermore, IDSR has been described as inconsistent and lacking in resources [8]. There is significant variation in how it is implemented across provinces. The system suffers from a shortage of trained epidemiological staff, poor coordination between provincial and federal authorities, and limited financial resources [8]. These issues weaken routine data collection and timely response efforts. As a result, by the time data are compiled and analyzed, community transmission is often already widespread. This reduces chances for early intervention [8].

To address these gaps, several countries have used digital tools for early outbreak detection. Google Trends is one such platform that gives real-time data on how often people search for specific terms [9]. Research from countries like India and Indonesia has shown that increases in dengue-related searches often happen before official numbers rise (9–12). For instance, studies in India found that online searches for "dengue symptoms" increased around 4 weeks before confirmed outbreaks [12]. This suggests that how people search for information may signal early signs of disease spread.

In Pakistan, internet access has grown quickly over the last ten years, with approximately 27% of the population now using the internet [13]. This digital data could offer useful insights into public health trends. However, there is little research on whether Google search activity can help predict dengue outbreaks locally.

This study aims to investigate the connection between Google Trends data and reported dengue case counts in Pakistan during 2024. By looking at weekly search interest for dengue-related terms and comparing it with official data from the IDSR system, this research examines if online search behavior can act as an early warning sign for upcoming outbreaks.

Methods

Data Sources

Weekly data on dengue case counts in Pakistan for 2024 came from the IDSR Weekly Bulletin. This bulletin is published by the National Institutes of Health (NIH) Pakistan through its Public Health Bulletin portal (https://phb.nih.org.pk/integratedisease-surveillance-and-response). The IDSR bulletin gathers weekly reports from provincial and district health departments throughout Pakistan, covering both public and private healthcare facilities. These reports include the counts of laboratory-confirmed and suspected dengue cases from all participating districts primarily using NS1 antigen, ELISA, IgM/IgG serology, and RT-PCR where available. However, laboratory confirmation coverage remains uneven across provinces, which can delay accurate case reporting. A substantial proportion of dengue infections are mildly symptomatic, which means true transmission may be even higher than reported.

Weekly Google Trends data were gathered from the Google Trends platform (https://trends.google.com) for the search terms "dengue fever," "dengue symptoms," "dengue treatment," and "dengue." The selection of search terms was informed by prior literature. The data were extracted at weekly granularity for the period January to December 2024, selecting Pakistan as the region of interest. Google Trends provides

Relative Search Volume (RSV) values from 0 to 100, with 100 representing the week that had the highest search frequency for the selected term.

Both datasets are publicly available and do not contain any personally identifiable information. Therefore, no ethical approval was needed.

Data Processing and Normalization

The IDSR case count data and Google Trends data were entered into Microsoft Excel and then imported into R version 4.3.3 for analysis.

Since Google Trends scores are scaled between 0 and 100 while case counts vary in absolute magnitude, the case count data were normalized to make both series comparable.
For each weekly value xi of dengue case counts, the normalized value y_i was computed as:

$$y_i = \frac{x_i}{x_{max}} \times 100$$

Where x_{max} is the maximum weekly case count in 2024.
This rescaling ensured that both datasets shared a common 0–100 scale.

Statistical Analysis

Correlational Analysis

All analyses were performed in R version 4.3.3 using the stats, zoo, and vars packages.
To assess the strength and direction of the relationship between Google search interest and dengue case count data, Pearson's product–moment correlation coefficient (r) was calculated separately for each search term. Two-tailed significance tests were conducted, and 95% confidence intervals (CI) were obtained.

Time-Series and Causality Analysis

Stationarity testing

Before causality testing, the Augmented Dickey–Fuller (ADF) test was applied to each time series to check for stationarity. Weekly Google Trends data for the search terms "dengue fever," "dengue symptoms," "dengue treatment," and "dengue" were analyzed alongside normalized dengue case count data from the IDSR system. A series was considered non-stationary when the ADF p-value > 0.05. Non-stationary series were differenced until stationarity was achieved.

The maximum differencing order dmax required across all series was used in the Toda–Yamamoto procedure.

Model specification and lag selection

A Vector Autoregression (VAR) model was constructed for each pairing of Google Trends data and normalized dengue case count data. The optimal lag length (k) was identified using multiple information criteria, including the Akaike Information Criterion (AIC), Hannan–Quinn (HQ), and Final Prediction Error (FPE) statistics. For the 2024 dataset, both AIC and HQ consistently indicated an optimal lag length of two weeks. This lag order was applied uniformly across all models to ensure consistency, comparability, and overall model stability. An augmented VAR with p=k+ dmax lags was used for the Toda–Yamamoto causality test.

Toda–Yamamoto causality test

The Toda–Yamamoto approach was employed to examine whether variations in Google search activity Granger-cause changes in dengue case counts. For each model, the null hypothesis stated that the Google Trends relative search volume (RSV) for a given term does not Granger-cause a rise in dengue case counts. Causality was evaluated using the modified Wald (MWALD) test applied to the coefficients of the augmented vector autoregressive (VAR) model. Statistical significance was defined at $p < 0.05$. The analysis generated F-statistics, degrees of freedom (df, df), and corresponding p-values for each model. In addition, instantaneous causality between variables was assessed using the same procedure to determine whether simultaneous relationships existed between Google search activity and dengue case count data.

Visualization

Weekly trends of each search term and dengue case count data were plotted, showing both raw and smoothed (3-week moving average) lines to illustrate synchronous or lagged patterns. Additionally, separate scatter plots were produced for each search term to depict linear correlations, with regression lines shown as dashed overlays.

Distinct color palettes were used to differentiate each search term: red ("dengue fever"), blue ("dengue symptoms"), green ("dengue treatment"), and purple ("dengue").

Results

Correlation between Google Trends data and dengue case counts

A strong positive correlation was observed between weekly Google search interest for dengue-related terms and normalized dengue case count data in Pakistan during 2024. As shown in Table 1, the Pearson correlation coefficients ranged from 0.756 to 0.832 ($p < 0.001$ for all). The highest correlation was seen for the general search term "dengue" ($r = 0.832$; 95% CI = 0.724–0.901), followed by "dengue symptoms" ($r = 0.786$; 95% CI = 0.653–0.872), "dengue treatment" ($r = 0.775$; 95% CI = 0.637–0.865), and "dengue fever" ($r = 0.756$; 95% CI = 0.608–0.853).

These results indicate that as public search activity for dengue-related terms increased online, reported dengue case counts also rose. Line plots with 3-week moving averages (Figures 1–4) and scatter plots comparing Google Trends and IDSR data (Figure 5) both demonstrated clear synchronous patterns and positive linear relationships between online search interest and outbreak counts, reinforcing the observed correlations.

Causality analysis using the Toda–Yamamoto test
Before applying the Toda–Yamamoto causality test, the stationarity of each time series was examined using the Augmented Dickey–Fuller (ADF) test. The ADF test results indicated that all series were non-stationary in level form, with $p > 0.05$ ("dengue fever": Dickey–Fuller = −1.93; lag order = 3; $p = 0.60$; "dengue symptoms": Dickey–Fuller = −1.52; lag order = 3; $p = 0.77$; "dengue treatment": Dickey–Fuller = −1.43; lag order = 3; $p = 0.80$; "dengue": Dickey–Fuller = −2.75; lag order = 3; $p = 0.27$; IDSR: Dickey–Fuller = −1.57; lag order = 3; $p = 0.75$). After first differencing, all series remained non-stationary ($p > 0.05$ for all variables). However, after second-order differencing, the data became stationary ("dengue fever": Dickey–Fuller = −5.47; lag order = 3; $p < 0.01$; "dengue symptoms": Dickey–Fuller = −5.03; lag order = 3; $p < 0.01$; "dengue treatment": Dickey–Fuller = −5.35; lag order = 3; $p < 0.01$; "dengue": Dickey–Fuller = −3.62; lag order = 3; $p = 0.04$; IDSR: Dickey–Fuller = −5.19; lag order = 3; $p < 0.01$). The maximum differencing order required to achieve stationarity across all variables was dmax = 2.

No cointegration was observed between the Google Trends and IDSR series, confirming the appropriateness of the Toda–Yamamoto causality framework without requiring cointegration adjustments. A Vector Autoregressive (VAR) model was then constructed for each pairing of Google Trends data and IDSR case count data. The optimal lag length (k) was determined using multiple information criteria, including the AIC, HQ, and FPE statistics, all of which consistently indicated an optimal lag of two weeks. Accordingly, an augmented VAR model with $p=k+\text{dmax} = 4$ was applied for each term.

Causality was assessed using the modified Wald (MWALD) test on the augmented VAR coefficients, with significance defined at $p < 0.05$. As shown in Table 2, significant Granger causality was observed for the search terms "dengue symptoms" ($F = 4.18$; $p = 0.004$), "dengue treatment" ($F = 5.10$; $p = 0.001$), and "dengue" ($F = 4.24$; $p = 0.004$), indicating that increases in online search activity preceded corresponding rises in reported dengue case counts. The observed time lag between Google search activity and reported dengue cases correlates well with the incubation periods of dengue virus transmission. The association for "dengue fever" was borderline ($F = 2.41$; $p = 0.056$). Instantaneous causality tests were non-significant across all models ($p > 0.05$), suggesting that relationships between search activity and case count data occurred with a time lag rather than simultaneously.

Discussion
This study looked at how Google Trends data could support Pakistan's national dengue surveillance system by tracking public search activity related to dengue over time. A strong positive relationship was found between weekly Google search interest and normalized case count data from the IDSR system, ($r = 0.76$–0.83, $p < 0.001$), with the term "dengue" demonstrating the strongest association. These findings indicate that as dengue transmission rises, people start searching online for information about illnesses, reflecting real-world disease trends in near real time.

The Toda-Yamamoto causality analysis showed that search activity can precede reported rises in case counts. Significant Granger causality appeared for "dengue symptoms" ($p = 0.004$), "dengue treatment" ($p = 0.001$), and "dengue" ($p = 0.004$), while "dengue fever" had a borderline association ($p = 0.056$). These findings suggest that rises in Google search interest usually happen weeks before officially reported rises in dengue cases. This supports the idea that digital search data could serve as an early warning tool for dengue surveillance in Pakistan.
Our findings align with research from other regions where dengue is common. In India, Singh et al. (2025) found a strong link between dengue-related Google searches and IDSP case counts ($r \approx 0.83$). Searches began to rise weeks before reported peaks [10,12]. Similarly, Verma et al. (2018) noted a lag of -2 to -3 weeks between search trends and surveillance data [9]. Other studies, including those by Sylvestre et al. and Ho et al., have shown similar correlations and time-lag patterns, usually ranging from 1 to 3 weeks [14,15]. These consistent time-lags suggest that public concern and the desire for information grow early in the outbreak—often during the phase when transmission starts to speed up but case reporting systems have not yet captured the increase. This closely matches our observed lag of 2 weeks and supports the idea that online search patterns can serve as real-time early indicators of transmission.

Comparable associations and predictive effects have also been reported in Indonesia (Husnayain et al., 2019), Brazil (Romero-Alvarez et al., 2020), and Mexico (Gluskin et al., 2014). This is especially true in urban areas where internet use is high and online health-seeking behavior is more common [11,16,17]. These patterns highlight an important contextual factor: the predictive value of Google Trends seems strongest in regions with high population density, active digital engagement, and frequent seasonal dengue outbreaks. These conditions are similar to major Pakistani cities like Karachi, Lahore, and Rawalpindi. Overall, these studies show a broader global trend: digital search activity not only reflects official rises in case count data but often comes before it. This supports its role as a useful and scalable early-warning signal in national surveillance systems.

A major strength of this study is its demonstration of how digital epidemiology can significantly improve Pakistan's existing dengue surveillance system. Unlike traditional case reporting, which often faces delays due to laboratory confirmation, clinical triage capacity, and administrative processing, Google Trends data are publicly available, free, and updated in real time. This allows for earlier situational awareness. Importantly, our analysis used national IDSR surveillance data, ensuring that the correlations we observed reflect actual public health reporting rather than indirect indicators. The use of multiple search terms and both correlation and causality approaches, including Toda-Yamamoto testing, further strengthens our findings. This reduces the chance that the observed associations resulted from coincidence, short-term media spikes, or seasonal awareness alone. This method does not need extra laboratory or field resources, making it scalable and practical for routine integration into outbreak monitoring workflows. In places like Pakistan, where reporting delays, a substandard surveillance system and uneven access to diagnostics are ongoing challenges, this approach offers a useful, low-cost way to achieve earlier detection, quicker risk communication, entomological surveillance, trigger vector control, diagnostic preparedness and a more proactive response to outbreaks [8,9,18,19].

A key practical implication of this approach is its potential role in laboratory diagnostic preparedness. Rising Google search activity for terms such as "dengue symptoms" or "dengue treatment" may alert diagnostic laboratories to an impending increase in testing demand before official case reports peak. This could support early procurement of NS1 antigen kits, IgM/IgG ELISA reagents, RT-PCR supplies, sample collection materials, and blood count testing capacity. It may also help laboratories plan staffing, extend testing hours, prioritize turnaround time, and coordinate reporting pathways with public health authorities. Therefore, Google Trends should not be viewed only as an epidemiological signal, but as a low-cost trigger for laboratory readiness during dengue season.

At the same time, a few limitations should be considered. The observed approximate two-week lag between search activity and reported IDSR data should be interpreted cautiously. While it may partly reflect the clinical course of dengue and the interval between symptom onset and healthcare-seeking behavior, it is also likely influenced by delays in healthcare presentation, laboratory confirmation, and administrative reporting within Pakistan's passive surveillance system. Therefore, the observed lag probably represents a combination of biological and reporting factors rather than the incubation period alone.

Furthermore, Google Trends shows patterns in public search interest, which may be affected by media coverage or awareness campaigns, along with actual infection rates [20]. Additionally, internet access and digital skills are often more concentrated in urban areas. This means search activity might not fully show trends in rural or remote regions. Lastly, this study covered a single year period. While the 2024 weekly data captured seasonal trends, the relatively small sample size may reduce the stability of the VAR lag selection and Toda–Yamamoto causality tests. Consequently, these forecasting results should be treated as preliminary evidence of temporal associations rather than conclusive predictive outcomes. Looking at multi-year datasets covering several dengue seasons, and including more data sources like climate factors, vector numbers, or reports from provinces, would help further validate and improve the method. Overall, these points underline areas for future work while still supporting the usefulness of Google Trends as a helpful tool in dengue surveillance.

Conclusion

This study shows that Google Trends can be a useful and low-cost addition to Pakistan's dengue surveillance system. The strong link and clear time-lag relationship between search activity and reported case counts indicate that people's online behavior reflects real changes in disease spread and can even help predict them. By watching for increases in dengue-related searches, health authorities could receive early warning signals before hospital cases rise. While Google Trends shouldn't replace official reporting, combining it with existing systems like the IDSR and incorporating Google Trends with microbiological data such as RT-PCR positivity rates, NS1 antigen trends, and circulating serotypes could create a multilayered early warning system which could make outbreak monitoring faster and more responsive. Future studies should look at data from multiple years, include regional comparisons, and connect digital data with weather and mosquito surveillance to build better early warning models.

Table 1: Pearson correlation between weekly Google search interest for dengue-related terms and normalized IDSR dengue outbreak data in Pakistan (2024).

Search Term	Pearson's *r*	95% Confidence Interval	*p*-value	Strength of Correlation
Dengue Fever	0.756	0.608–0.853	< 0.001	Strong positive
Dengue Symptoms	0.786	0.653–0.872	< 0.001	Strong positive
Dengue Treatment	0.775	0.637–0.865	< 0.001	Strong positive
Dengue	0.832	0.724–0.901	< 0.001	Strong positive

Table 2: Toda–Yamamoto causality test results for weekly Google search interest and normalized dengue outbreak data in Pakistan (2024).

Search Term	F-statistic	df_1	df_2	p-value	Interpretation
Dengue Fever	2.41	4	78	0.056	Borderline causality (not statistically significant)
Dengue Symptoms	4.18	4	78	0.004	Significant causality (searches predict outbreaks)
Dengue Treatment	5.10	4	78	0.001	Significant causality (searches predict outbreaks)
Dengue	4.24	4	78	0.004	Significant causality (searches predict outbreaks)

Figure 1: Weekly Google Trends (GT) search interest for "dengue fever" and normalized IDSR dengue case count data in Pakistan (2024). The figure presents both raw values and 3-week moving averages for comparative trend analysis.

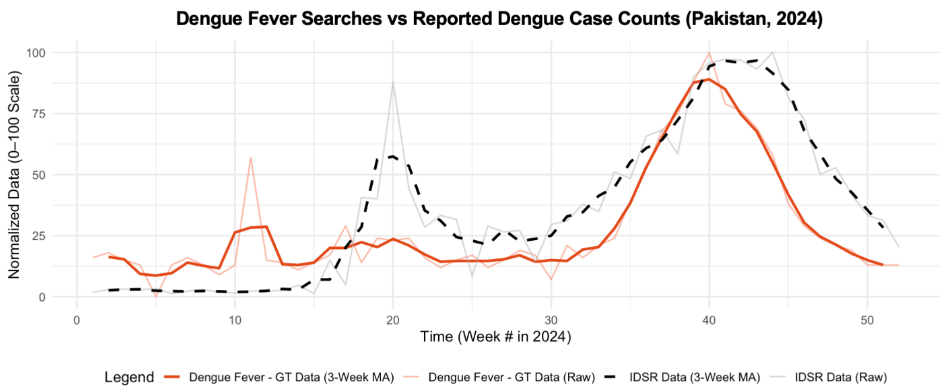


Figure 2: Weekly Google Trends (GT) search interest for "dengue symptoms" and normalized IDSR dengue case count data in Pakistan (2024). The figure presents both raw values and 3-week moving averages for comparative trend analysis.

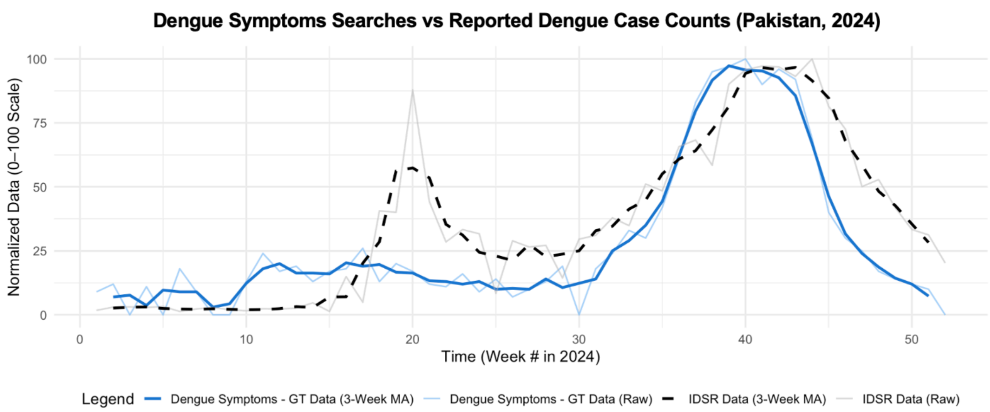


Figure 3: Weekly Google Trends (GT) search interest for "dengue treatment" and normalized IDSR dengue case count data in Pakistan (2024). The figure presents both raw values and 3-week moving averages for comparative trend analysis.

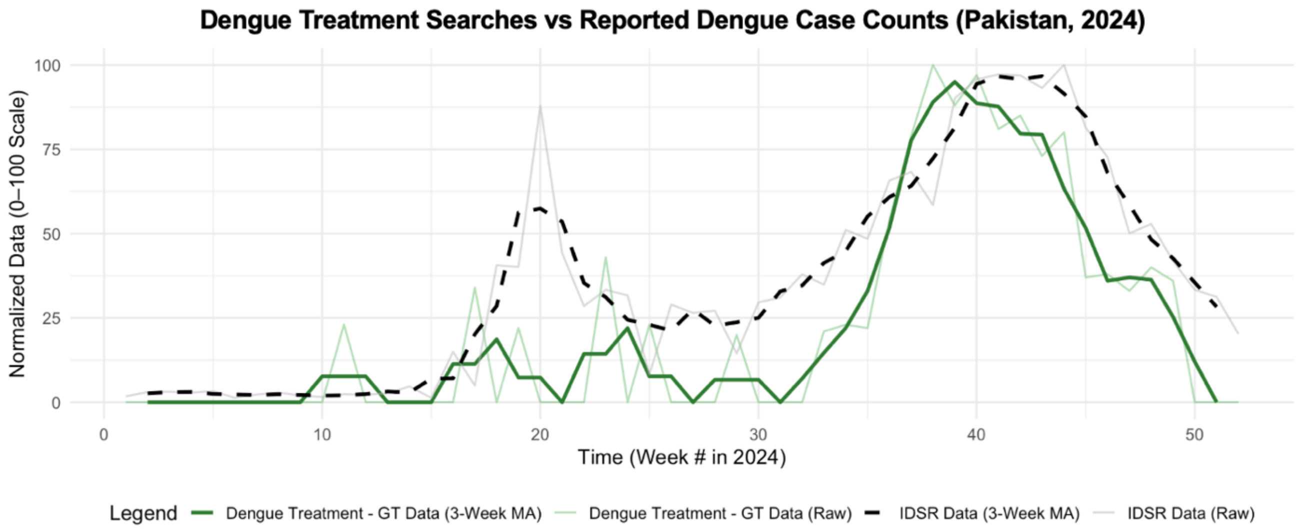


Figure 4: Weekly Google Trends (GT) search interest for "dengue" and normalized IDSR dengue case count data in Pakistan (2024). The figure presents both raw values and 3-week moving averages for comparative trend analysis.

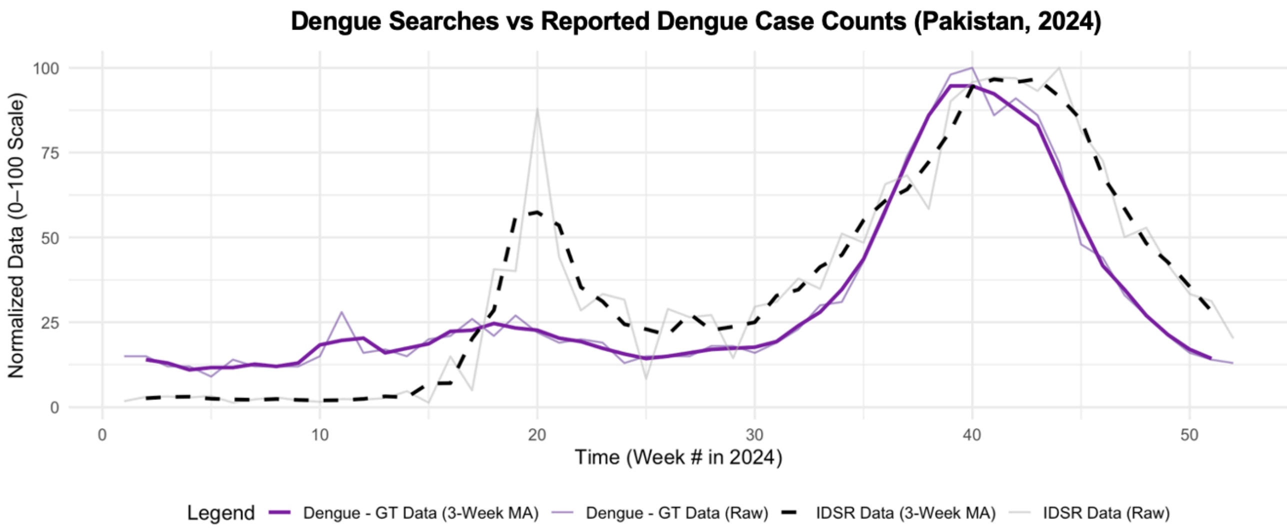
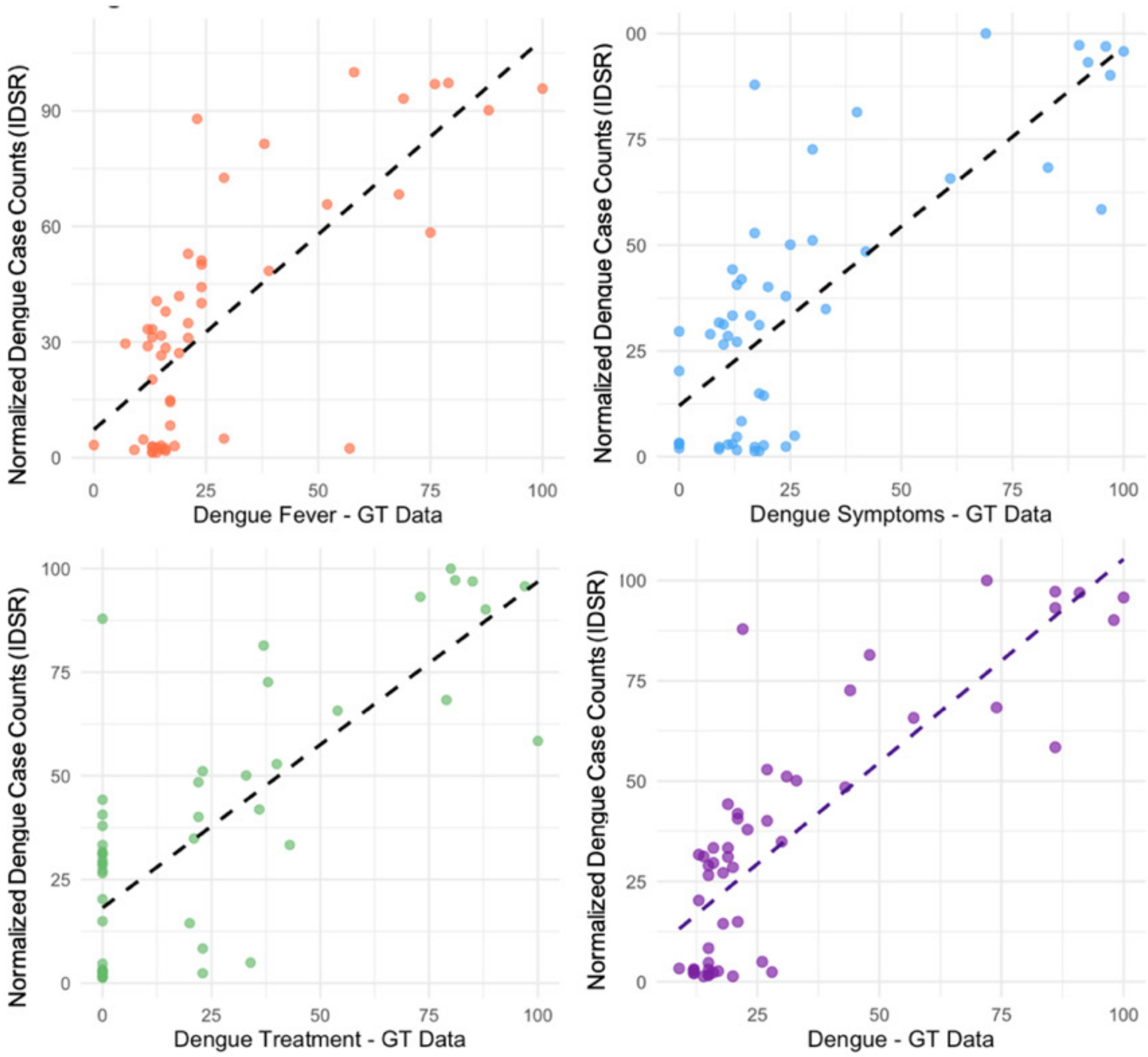


Figure 5: Scatter plots showing the relationship between Google Trends (GT) search interest and normalized dengue case count data (IDSR) in Pakistan during 2024. The top left, top right, bottom left, and bottom right panels represent plots for search terms: “Dengue Fever”, “Dengue Symptoms”, “Dengue Treatment”, and “Dengue”, respectively. The dashed line in each plot represents the linear regression line, illustrating the strong positive association between Google search activity and reported dengue case counts.



Conflicts of Interests

All authors declare no conflicts of interest.

Ethical Approval

Not required as publicly available data.

Credit Author Statements

Alizeh Sonia Fatimi did the data search, data analysis, and drafting of the manuscript. Tazeen Fatima, Asghar Nasir, Muhammad Shariq Shaikh, and Imran Siddiqui contributed to manuscript writing, graphs and critical revisions. Sibtain Ahmed conceived the primary idea for the work, supervised the overall project.

Funding

None.

Data Availability

Publicly available data was analysed.

References

1. Dengue worldwide overview [Internet]. Available from: https://www.ecdc.europa.eu/en/dengue-monthly. Accessed: 03/11/2025.
2. Guzman MG, Harris E. Dengue. Lancet. 2015;385(9966):453–465.
3. Khan J, Khan I, Ghaffar A, Khalid B. Epidemiological trends and risk factors associated with dengue disease in Pakistan (1980–2014): a systematic literature search and analysis. BMC Public Health. 2018;18(1):745.
4. National Institute of Health, Pakistan. Advisory for the prevention and control of dengue fever. Islamabad: Center for Disease Control, Ministry of National Health Services, Regulations & Coordination; 2025.
5. Rafique I, Nadeem Saqib MA, Munir MA, Qureshi H, Siddiqui S, Habibullah S, et al. Economic burden of dengue in four major cities of Pakistan during 2011. J Pak Med Assoc. 2015;65(3):256–259.
6. Hussain M, Majeed A, Imran I, Rasool MF, Hussain I, Ghaffar A, et al. Dengue control in Pakistan: prior planning is better than controlling too late. BMJ. 2019;367:l6912.
7. Haq ZU, Fazid S, Hussain B, Khan MF, Betanni A, Behrawar B, et al. Assessment of the impact of integrated disease surveillance and response system on surveillance management at healthcare facilities in Pakistan. East Mediterr Health J. 2024;30(2):109–115.
8. Shaikh TG, Waseem S, Ahmed SH, Swed S, Hasan MM. Infectious disease surveillance system in Pakistan: challenges and way forward. Trop Med Health. 2022;50(1):46.
9. Verma M, Kishore K, Kumar M, Sondh AR, Aggarwal G, Kathirvel S. Google search trends predicting disease outbreaks: an analysis from India. Healthc Inform Res. 2018;24(4):300–308.
10. Thamaraikannan R, Munisamy V. Using Google Trends for dengue surveillance and epidemiological research. Int J Community Med Public Health. 2022;9(10):3917.
11. Husnayain A, Fuad A, Lazuardi L. Correlation between Google Trends on dengue fever and national surveillance report in Indonesia. Glob Health Action. 2019;12(1):1552652.
12. Singh G, Jha A, Aadil MK. Analyzing the relationship between Google Trends data and dengue outbreaks: a causality and correlation study. Discover Public Health. 2025;22(1):320.
13. Individuals using the Internet (% of population) – Pakistan [Internet]. Available from: https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=PK. Accessed: 03/11/2025.
14. Ho HT, Carvajal TM, Bautista JR, Capistrano JDR, Viacrusis KM, Hernandez LFT, et al. Using Google Trends to examine the spatio-temporal incidence and behavioral patterns of dengue disease: a case study in Metropolitan Manila, Philippines. Trop Med Infect Dis. 2018;3(4):118.
15. Sylvestre E, Cécilia-Joseph E, Bouzillé G, Najioullah F, Etienne M, Malouines F, et al. The role of heterogeneous real-world data for dengue surveillance in Martinique: observational retrospective study. JMIR Public Health Surveill. 2022;8(12):e37122.
16. Gluskin RT, Johansson MA, Santillana M, Brownstein JS. Evaluation of Internet-based dengue query data: Google Dengue Trends. PLoS Negl Trop Dis. 2014;8(2):e2713.
17. Romero-Alvarez D, Parikh N, Osthus D, Martinez K, Generous N, del Valle S, et al. Google Health Trends performance reflecting dengue incidence for the Brazilian states. BMC Infect Dis. 2020;20(1):252.
18. Wang D, Guerra A, Wittke F, Lang JC, Bakker K, Lee AW, et al. Real-time monitoring of infectious disease outbreaks with a combination of Google Trends search results and the moving epidemic method: a respiratory syncytial virus case study. Trop Med Infect Dis. 2023;8(2):75.
19. Satpathy P, Kumar S, Prasad P. Suitability of Google Trends for digital surveillance during ongoing COVID-19 epidemic: a case study from India. Disaster Med Public Health Prep. 2021;17:e28.
20. Chan EH, Sahai V, Conrad C, Brownstein JS. Using web search query data to monitor dengue epidemics: a new model for neglected tropical disease surveillance. PLoS Negl Trop Dis. 2011;5(5):e1206.