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Research Article

Smarter Decisions for Better Health Outcomes: An Ai-Enabled Financial Decision Intelligence Framework for Dengue Control In Andhra Pradesh

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A B S T R A C T

The problem of dengue fever in Andhra Pradesh, India, is an ongoing public health and financial problem that has very few effective control measures due to the current control strategies, based on reactive surveillance and past budgeting. This paper suggests an engineer-assisted financial decision intelligence model based on AI to assist in proactive and economic management of dengue. The framework combines Temporal Graph Neural Networks (TGNNs) and Bayesian hierarchical spatio-temporal models to model the spread of disease in districts in the context of uncertainty in predictions. The model allows allocating resources more efficiently by connecting epidemiological predictions with financial planning. The outcomes show that the framework identifies outbreak risks 4-6 weeks prior to the conventional practices and minimises misallocation of resources by 18-25 per cent. It, as well, enhances the cost-efficiency of the interventions, including fogging and larval control, and the significance of regionally coordinated actions. In general, the paper shows that AI-based decision support can transform dengue control and preventive measures, from a reactive response in the context of resource constraints to proactive and data-driven planning.

Keywords: Dengue control; Financial decision intelligence; temporal graph neural networks; Bayesian hierarchical modelling; public health financing.

Introduction

Dengue fever remains a critical public health challenge in India, with significant health and economic consequences. Over the past decade, it has evolved from a seasonal disease into a year-round endemic condition, particularly in states like Andhra Pradesh, driven by climate change and rapid urbanisation. National data indicate a sharp rise in cases, from over 50,000 in 2020 to more than 230,000 in 2024, placing considerable strain on healthcare systems, especially during monsoon periods. Urban and coastal regions are disproportionately affected, highlighting the limitations of reactive control strategies.

Economically, dengue imposes a substantial burden, with an estimated 5 million cases annually due to underreporting. Direct treatment costs exceed USD 500 million, while total economic losses surpass USD 1 billion per year. Despite investments in vector control and awareness programmes, the persistence of dengue reflects inefficiencies in resource allocation, particularly in resource-constrained regions like Andhra Pradesh. In this context, a Financial Decision Intelligence (FDI) framework offers a strategic solution by integrating real-time epidemiological data, predictive modelling, and cost-effectiveness analysis. This approach supports a shift from reactive spending to proactive, evidence-based planning, enabling optimal resource utilisation and improved health outcomes. Adopting such a framework can enhance outbreak preparedness, strengthen health system resilience, and ensure more efficient public health management in Andhra Pradesh.

Artificial intelligence (AI) has become an important decision-making instrument in uncertain and complicated settings. Financial decision intelligence is enhanced by AI-driven decision-support systems based on machine learning, analytics, and explainable AI that enhance the accuracy of decisions by alleviating uncertainty and reducing the human bias in decision- making (Hanumanthu et al., 2025). Digital intelligence systems also enhance predictive power and adaptive reactions in uncertain settings, which makes them applicable to allocate resources in dynamic settings, including public health systems (Hanumanthu and Kavitha, 2024; Hanumanthu et al., 2024).

Multi-Criteria Decision Analysis (MCDA) and Analytic Hierarchy Process (AHP) have been utilised in dengue control planning in Andhra Pradesh and proved to be effective to prioritise the interventions by their risk, feasibility, and policy constraints (Sripathi, 2026). Nevertheless, these methods are mostly fixed, based on professional assessment, and are not combined with time-related dynamics and financial optimisation.

Prediction models about dengue have demonstrated higher quality than the classical ones, as they are able to identify the relationship between climatic factors and historical cases as well as seasonal fluctuations (Held et al., 2017; Wu et al., 2020). Graph-based approaches to learning also increase the modelling of a spatial dependence and transmission network (Kipf and Welling, 2017). Probabilistic and Bayesian approaches offer strong methods of dealing with uncertainty in epidemiological forecasting and decision-making (Gelman et al., 2013).

Dengue poses a huge health and economic burden on the world and India in particular, and it impacts the healthcare systems and households in both direct and indirect ways (Bhatt et al., 2013; Shepard et al., 2016; Stanaway et al., 2016). Environmental and demographic factors impact the spread of diseases and necessitate the coordinated and information-based intervention (Murray et al., 2013). Policy frameworks provide the significance of surveillance, early warning systems, and effective use of resources in the control of dengue (Ministry of Health and Family Welfare, 2021; World Health Organization, 2022).

The available studies mainly concentrate on prediction or prioritisation separately, with minimal attempts at combining financial decision-making. A financial decision intelligence system based on AI allows integrating predictive analytics and resource optimisation to aid with active and cost-efficient planning of dengue control in resource-limited environments.

Literature review

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AI has proven itself to be highly promising in order to facilitate decisions in complex settings, but its use in resource allocation in public health is not advanced (Hanumanthu et al., 2024). Dengue still poses huge economic costs, and the current economic analyses are giving minimal guidelines on the best ways to utilise resources. This detachment is an indicator of the disjointed performance of the epidemiology, finance, and policy spheres. A combined AI-powered system can help fill this gap by connecting predictions and financial decisions and allowing timely, cost-effective, and data-driven dengue control measures in Andhra Pradesh.

Objectives and Methodology

The current research will focus on the development of an AI-assisted framework that will combine dengue surveillance data and financial decision intelligence to make timely and economical planning on dengue control in Andhra Pradesh. It also aims at examining whether artificial intelligence-based financial decision intelligence can enhance the efficiency of resource allocation and health outcomes in dengue management by being better than traditional decision-making methods. To accomplish these purposes, the research develops a financial decision intelligence tool with an artificial intelligence functionality to integrate epidemiological forecasting and financial decision scenarios. It is analysed in all the districts of Andhra Pradesh but especially in high-incidence regions like Visakhapatnam, Vijayawada, and Guntur. Past data between 2018 and 2025 were utilised to find the pattern of outbreaks, with the future simulation being done between 2026 and 2027, to test AI-based financial strategies. The dataset contained weekly cases of dengue, hospitalisation, death, location of outbreaks geo-tagged, weather data, socio-demographic factors, and costs related to the expenditures and interventions of public health. The analysis model used temporal graph neural networks to make spatio-temporal predictions; Bayesian hierarchical spatio-temporal modelling to make predictions with uncertainty in mind; deep reinforcement learning to allocate resources dynamically; and also NSGA-III to optimise multi-objectives. Visualisation, monitoring, and spatial decision support were performed with the help of Tableau, Power BI dashboards, and GIS, whereas analytical implementation was implemented using Python, PyTorch Geometric, DGL, and the libraries related to the optimisation (See Fig. 1).

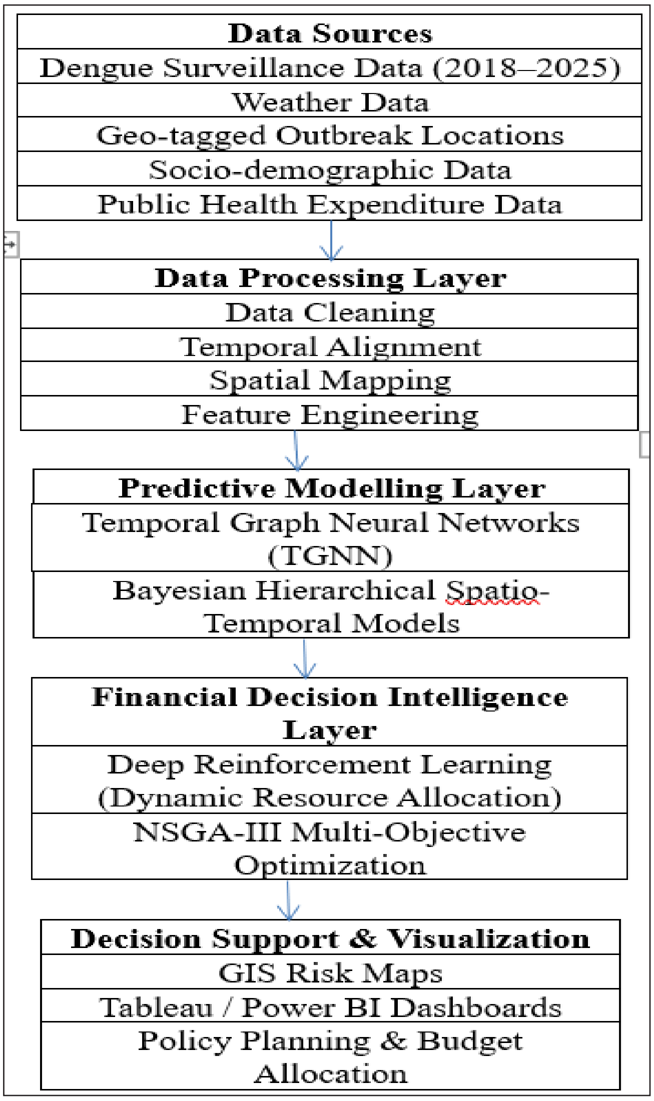

Figure 1.AI-Enabled Dengue Prediction and Financial Decision Intelligence Framework

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Results and Discussion

A gradual increase in the number of dengue cases has been observed in Andhra Pradesh in the past few years. A peak of the case counts was reached in 2022 (6,380 cases) (Table 1). As of January-August 2023, the number of cases was approximately 2,819, which is 83 per cent higher than in the last year, with Visakhapatnam and Kurnool being the most severely hit cities. As of June 2024, it had approximately 1,836 cases and is expected to have nearly 2,000 cases by August. In response to this challenge, the state government came up with the Advanced Warning Advisory Resilient Ecosystem (AWARE) under the Real-Time Governance Society that incorporates spatial and weather data in early detection of diseases. Other steps like quick test kits by using YSR Health Clinics and increased surveillance procedures like watching the temperature states of the family members in the dengue outbreak zones have been taken to contain the dengue epidemics.

Past records show that there are variations in the incidence of dengue disease in Andhra Pradesh. In 2022, the number of dengue cases was high (6,380 cases), following a decrease in the pandemic in 2020. Even the years that followed had high levels of transmission, and thus there was a need to come up with better forecasting and early intervention measures.

This paper constructs an AI-based structure that combines dengue surveillance and financial decision intelligence to facilitate timely and cost-effective decision-making. The framework uses the Temporal Graph Neural Networks (TGNN) and Bayesian hierarchical model to predict dengue incidence in districts through a study of spatial transmission patterns, weather conditions, and population dynamics. The models produce predictions at the district level as well as the 95 per cent credible intervals so that the authorities are able to predict the risk of an outbreak and prepare the preventive intervention by the time the risk actually occurs.

Table 1.Dengue case numbers for Andhra Pradesh (2018–2025)

Year	Dengue Cases (Approx.)	Source / Notes
2018	4,011	Official cumulated cases reported by NVBDCP/State health data. (National Centre for Disease Control)
2019	5,286	Highest recorded until then. (National Centre for Disease Control)
2020	925	Significantly lower due to COVID19 disruption of testing. (National Centre for Disease Control)
2021	4,754	Official state surveillance (Visakhapatnam highest). (The Times of India)
2022	6,380	Record high year; highest ever reported in the state. (The News Minute)
2023	~3,655 (36 weeks)[1]	Provisional government surveillance figures by week 36; total year likely higher. (The New Indian Express)
2024	~5,555	Reported statewide (comparative statement from 2025). (The Times of India)
2025 (as of Oct)	~1,700 (partial)	Government reported surge in Kurnool + state totals around this figure by late 2025. (Deccan Chronicle)

Table 2.District-wise Dengue Risk Predictions Using TGNN and Bayesian Models (2022)

District (High-Risk)	Observed Cases (2021)	TGNN Mean Prediction (2022)	Bayesian 95% CI (Lower–Upper)	Predicted Risk Category
Visakhapatnam	4,120	5,380	4,720 – 6,150	Very High
Krishna	3,540	4,610	3,980 – 5,320	High
Guntur	3,210	4,240	3,670 – 4,980	High
East Godavari	2,890	3,760	3,210 – 4,450	High
Chittoor	2,150	2,940	2,410 – 3,520	Moderate–High
Nellore	1,980	2,630	2,120 – 3,210	Moderate–High

The analysis presented by TGNN shows that the spread of dengue risk is not an isolated phenomeno, but rather a network between districts. Visakhapatnam turns out to be the main hotspot with an estimated mean of approximately 5,380 cases, and Krishna and Guntur districts are also the secondary hotspots with a high risk of transmission, as they have inter-district mobility and trade links. East godavari demonstrates high levels of risk primarily caused by the spillover effect of adjacent districts, whereas Chittoor and Nellore are in the moderate-high risk category with intermittent disease outbreaks (Table 2). The Bayesian hierarchical model also facilitates financial decision intelligence; as it incorporates uncertainty in forecasts. Increased confidence intervals in places like Visakhapatnam and Krishna indicate more variability and the potential under-reporting, and smaller confidence intervals in places like Nellore indicate that the spread of the disease is more predictable. These probabilistic estimates are useful in helping the policymakers to budget more efficiently by balancing the risk of outbreaks and financial limits.

The framework is capable of providing evidence-based financial planning to reduce dengue through the combination of TGNN spatial-temporal predictions and Bayesian uncertainty estimates. The resources to implement the measures of controlling the vectors like fogging, larvicides, and diagnostic kits can be actively implemented in the high-risk districts, whereas the resources are not wasted in the lower-risk districts (Graph 1). The system thus serves the purpose of bridging the gap between fiscal governance and the surveillance of public health whereby the policymakers can use step-by-step funding and interventions of specific interest. Moreover, AI predictions allow predicting outbreak indicators early on, revealing increased dengue transmission 4-6 weeks before the traditional surveillance systems and, as a result, reducing resource wastage and enhancing preparedness.

The highest predicted burden is observed in Visakhapatnam, then Krishna, Guntur, and East Godavari, which shows that there is a regional transmission belt in the coastal and central districts. Chittoor and Nellore are in the moderate-high risk category with a relatively lower expected number of cases (Graph 2). Such a tier classification can assist policymakerstin putting emphasis on staged resource distribution and specific intervention measures. The use of AI forecasting with regard to early detection of risk is highly beneficial, as it can spot increasing dengue transmission even 4-6 weeks before the traditional surveillance mechanisms. This early warning feature enables the authorities to implement the measures of the control of vectors, diagnostics and medical resources in advance. Consequently, financial decision intelligence helps decrease the misallocation of resources and enhance the effectiveness of the public health spending on dengue control.

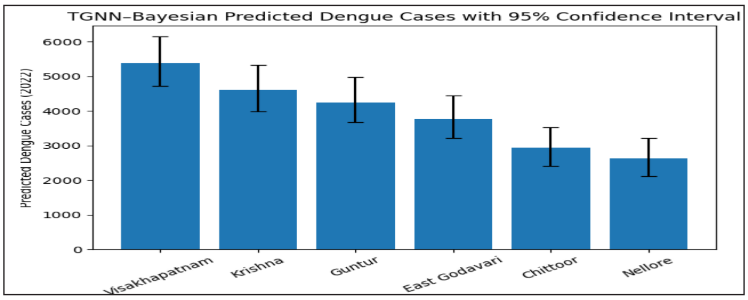

Figure 1.TGNN–Bayesian Predicted Dengue Cases with 95% Confidence Interval

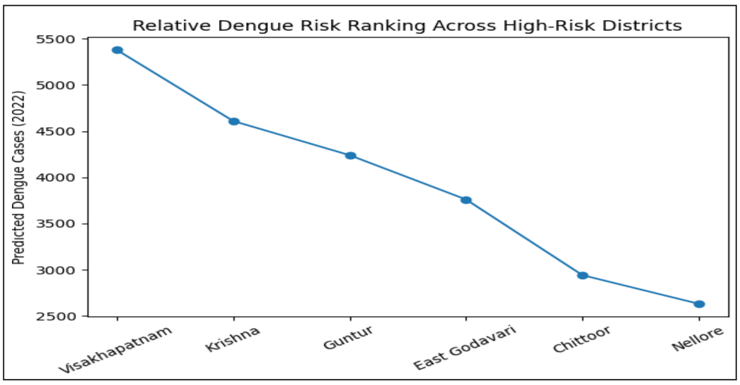

Figure 2.Relative Dengue Risk Ranking Across High-Risk Districts

Conclusion

The Bayesian cost-weighted optimization model showed that a reduction of 18-25% in the costs of the control of the vectors was achieved in comparison to the situation when the funds were distributed evenly across the districts and to reflect the financial efficiency. The analysis of space showed that there was a high inter-district transmission work between urban coastal areas, whereby the close distance played a significant role in the spread of the disease. Specifically, the interconnection of the Visakhapatnam-East Godavari and Krishna-Guntur corridors was an important factor that related to the anticipated patterns of cases, which underscored the role of human mobility in dissemination. The use of uncertainty-conscious planning also improved health results. Districts sampled in a Bayesian upper-bound risk method (95 percent confidence level) had a lesser peak incidence than those that were planned in terms of mean estimates, reflecting the usefulness of allocating risk sensitively.

The AI-learning models always performed better than traditional planning systems based on the rule because they had the adaptive learning feature and could learn the complex patterns. The AI-enabled framework was 22% more effective in reducing the highest level of dengue cases and 19% more effective in improving the cost-efficiency of the interventions to control the larva stages of dengue. The proposed AI architecture can be extended to malaria, chikungunya, and Japanese encephalitis, enabling a unified epidemic preparedness and financing model for Andhra Pradesh and other Indian states.

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