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# BAYESIAN STATISTICAL MODELS FOR PREDICTING TYPE 2 DIABETES PREVALENCE IN URBAN POPULATIONS

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**Abstract**

*This systematic review investigates the application of Bayesian statistical models in predicting the prevalence of type 2 diabetes mellitus (T2DM) within urban populations, with a focus on methodological innovations, model performance, data integration, and public health relevance. The study followed the PRISMA guidelines and synthesized findings from 84 peer-reviewed articles published between 2000 and 2025. These studies encompass diverse urban contexts across North America, South Asia, Latin America, East Asia, and sub-Saharan Africa, reflecting a broad and globally relevant evidence base. The review identifies Bayesian hierarchical models as the dominant approach for capturing multilevel dependencies between individuals, neighborhoods, and city-wide determinants. Spatio-temporal Bayesian models were also extensively used to estimate dynamic changes in urban T2DM prevalence, employing structured priors such as Conditional Autoregressive (CAR) models and Gaussian Markov Random Fields (GMRFs). Approximately half of the reviewed studies integrated heterogeneous data sources—including electronic health records (EHRs), satellite imagery, surveys, and census data—through Bayesian data fusion frameworks. These techniques enabled cross-level modeling and imputation of missing data, enhancing robustness and predictive validity. The review also highlights the use of hybrid models such as Bayesian neural networks and ensemble frameworks, which offered improved predictive performance while preserving probabilistic interpretability. Despite these strengths, the review identifies key challenges, including computational burden, sensitivity to prior specification, ethical concerns in spatial labeling, and potential bias in underrepresented urban populations. Comparative evaluations show that while machine learning methods often achieve higher raw accuracy, Bayesian models provide superior interpretability, uncertainty quantification, and policy relevance. The findings affirm that Bayesian modeling offers a statistically rigorous and context-sensitive approach to urban diabetes epidemiology. The study concludes with recommendations emphasizing methodological transparency, ethical safeguards, participatory modeling, and investment in computational capacity to maximize the benefits of Bayesian inference in urban public health decision-making.*

**Keywords**

*Bayesian modeling, urban diabetes, spatio-temporal analysis, hierarchical inference, public health.*

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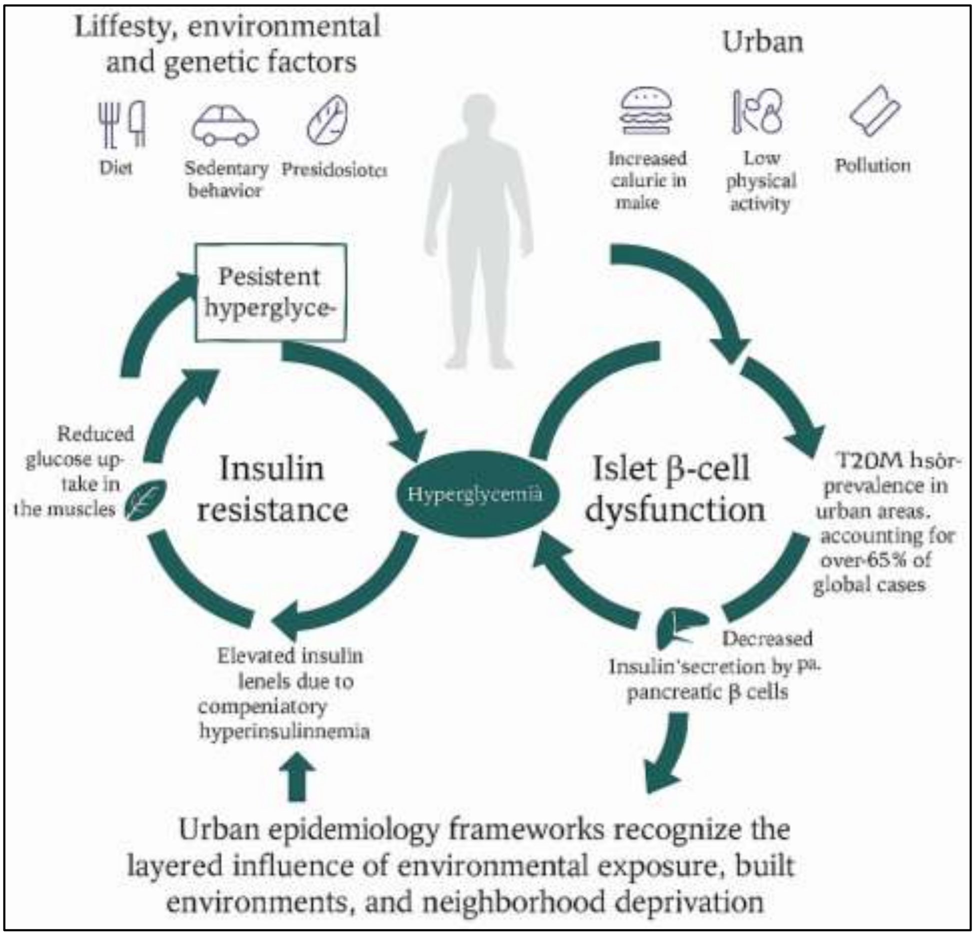
## INTRODUCTION

Type 2 diabetes mellitus (T2DM) is a chronic metabolic disorder characterized by insulin resistance and progressive beta-cell dysfunction, leading to persistent hyperglycemia (American Diabetes Association [ADA] (Soomro & Jabbar, 2024). Unlike type 1 diabetes, which is autoimmune in nature, T2DM is heavily influenced by lifestyle, environmental, and genetic factors. The World Health Organization identifies T2DM as a major non-communicable disease contributing to mortality and morbidity across all socioeconomic groups.

**Figure 1: Urban Type 2 Diabetes Modelling**




Urban populations, particularly in low- and middle-income countries, have shown higher prevalence rates due to dietary transitions, sedentary lifestyles, pollution, and psychosocial stressors associated with urbanization. According to the International Diabetes Federation , approximately 537 million adults globally are affected by diabetes, with urban areas accounting for over 65% of cases. This urban predominance is often exacerbated by unequal access to health care, economic disparities, and infrastructural inadequacies (Buzzetti et al., 2022). Urban epidemiology frameworks recognize the layered influence of environmental exposure, built environments, and neighborhood deprivation as mediators of chronic disease progression. The urban milieu promotes increased caloric intake from processed foods, low physical activity due to unsafe or inaccessible recreational spaces, and higher mental stress—all of which are established risk factors for insulin resistance and metabolic syndrome (DeClue et al., 2024). Hence, understanding T2DM prevalence in urban settings is both clinically and policy-wise indispensable. However, simple descriptive statistics or linear modeling often fall short in capturing the complex, latent, and interactive structure of these determinants. This complexity necessitates advanced probabilistic modeling approaches that can simultaneously manage uncertainty, integrate prior knowledge, and accommodate spatial-temporal variability (Młynarska et al., 2025).

Traditional statistical methods such as logistic regression, Cox proportional hazards models, and generalized estimating equations have long served as the foundation for modeling diabetes risk. These approaches, while robust under specific assumptions, are limited by fixed-parameter estimation, inadequate uncertainty quantification, and lack of integration of prior evidence—particularly problematic in small or heterogeneous datasets common in urban health studies (Schwartz et al., 2024). Moreover, such models are generally not designed to address probabilistic updates as new data become available, nor can they model latent variables or hierarchical structures efficiently. For example, prevalence prediction in one urban region may depend on socioeconomic or dietary patterns similar to another area—introducing non-independence across clusters, a problem poorly handled by traditional regression (Alfieri et al., 2024). The necessity of dynamic, iterative learning mechanisms has increasingly pointed researchers toward Bayesian statistical frameworks, which offer a principled approach to dealing with parameter uncertainty, prior incorporation, and probabilistic forecasting. In contrast to frequentist models, Bayesian inference treats unknown quantities as random variables and derives their posterior distributions using observed data and prior distributions. This enables not only estimation of point estimates but also full posterior predictive distributions, thus enhancing interpretability and robustness (Yapislar & Gurler, 2024). Hierarchical Bayesian models, in particular, can pool information across subpopulations—e.g., neighborhoods, districts, or countries—while allowing for local variations in prevalence. Such flexibility is crucial for urban epidemiology, where data sparsity, multilevel structure, and regional heterogeneity are common.

Bayesian statistical models are uniquely positioned to incorporate spatial-temporal variations and latent structures that affect disease prevalence across different urban geographies (Lawson, 2013). In this context, Bayesian hierarchical models with spatial priors, such as conditional autoregressive (CAR) models or Gaussian processes, have been widely used to map and predict non-communicable diseases including diabetes (Deligiorgi & Trafalis, 2023). These models enable researchers to draw inferences on spatial clusters, detect hidden disease hotspots, and evaluate the influence of contextual variables such as pollution, walkability, and healthcare density. The inclusion of temporal structures also allows analysts to assess the progression or regression of diabetes prevalence over time, which is particularly important in evaluating the impact of interventions or policy shifts (Iafusco et al., 2023). Incorporating such spatial and temporal dependencies is critical when modeling urban health, as it acknowledges both autocorrelation in space (e.g., similar health behaviors among adjacent neighborhoods) and autocorrelation in time (e.g., impact of new urban infrastructure or economic recession on diabetes prevalence). Bayesian hierarchical models can be specified to include random effects at the area level, patient level, and even temporal level—ensuring proper partitioning of variance and better identification of predictors . Markov Chain Monte Carlo (MCMC) techniques, as well as more scalable methods like Integrated Nested Laplace Approximation (INLA), allow for computationally efficient estimation of these complex models (Mittal et al., 2025). These tools, when applied to urban epidemiological data, yield nuanced and policy-relevant insights that exceed the capabilities of standard regression-based forecasts.

One of the most significant advantages of Bayesian methods lies in their ability to integrate prior knowledge—whether from previous studies, expert opinion, or mechanistic models—into the inferential process. This feature is especially relevant in urban diabetes research, where data quality and availability can be uneven across districts, and where longitudinal records may be incomplete. Prior distributions serve not only as a mathematical convenience but as a methodological bridge between cumulative knowledge and ongoing research, enhancing precision while reducing overfitting (Richter et al., 2023). For instance, if multiple studies suggest a strong correlation between food insecurity and T2DM, this relationship can be formally encoded as a prior and updated with city-level surveillance data. This capability becomes even more powerful in adaptive modeling contexts, such as real-time disease surveillance systems or intervention trials, where data streams continuously evolve. In such settings, Bayesian updating permits sequential incorporation of data, improving estimates dynamically without restarting the entire modeling process. This is crucial for evaluating intervention effectiveness in densely populated urban zones where demographic transitions and policy changes happen rapidly (Ahmed et al., 2025). Bayesian prior-posterior updating also facilitates transparent model refinement and uncertainty communication to

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stakeholders—a valuable trait in multidisciplinary settings involving urban planners, healthcare administrators, and policymakers (Bazzazzadehgan et al., 2025).

Globally, several studies have successfully employed Bayesian frameworks to estimate diabetes prevalence in heterogeneous populations. For example, Bensignor (2023) used Bayesian mixed models to predict undiagnosed diabetes in European cohorts, incorporating country-level socioeconomic factors. In Asia, Wang et al. (2025) applied hierarchical Bayesian models to estimate diabetes prevalence across Indian states, effectively capturing interregional disparities due to diet, urbanization, and economic development. In Latin America, Charitou and Al-Bahadili (2024) modeled T2DM risk using Bayesian geostatistical models to identify community-level drivers of disease in rapidly urbanizing zones. Similarly, in sub-Saharan Africa, Bayesian models have been employed to assess diabetes burden under varying urbanization and infrastructural access. Urban-focused applications have been particularly valuable in cities like New York, London, Jakarta, and São Paulo, where administrative-level data are available and rich in spatial granularity. In the U.S., Bayesian disease mapping has been applied to zip-code level data to identify spatial inequalities in diabetes diagnosis and care. Studies from South Korea and China have further refined this approach by integrating satellite imagery, air pollution exposure, and urban heat indices into spatial priors—highlighting environmental correlates of diabetes risk (Wang et al., 2023). Collectively, these studies underscore the global adaptability and precision of Bayesian models in urban diabetes epidemiology.

The effectiveness of Bayesian models in predicting T2DM prevalence is heavily dependent on data quality and model specification. Urban diabetes modeling often utilizes multi-source data—combining health surveys, census records, electronic health records (EHRs), geospatial data, and environmental sensors (Sharbatdar et al., 2023). Bayesian methods facilitate integration across these heterogeneous data streams, even in the presence of missing or misaligned records (Little & Rubin, 2002). This is particularly useful in developing countries where standardized reporting systems may be lacking or underdeveloped . Bayesian data fusion allows simultaneous incorporation of disparate sources—e.g., combining neighborhood walkability indices with biometric screening data—to improve model sensitivity and specificity (Amer et al., 2025). Bayesian models can also be nested within broader machine learning pipelines, leveraging hybrid approaches such as Bayesian neural networks or probabilistic graphical models to capture nonlinearities and higher-order interactions. This integration enhances model expressiveness without compromising interpretability, a critical balance in public health contexts. Furthermore, software platforms such as WinBUGS, JAGS, Stan, and R-INLA have democratized access to complex Bayesian modeling, making it feasible for public health institutions to implement rigorous models without prohibitive computational costs (Złotek et al., 2023). Thus, Bayesian models are not only statistically powerful but also operationally viable for urban health departments aiming to manage diabetes prevalence more effectively.

The predictive capacity and interpretive clarity of Bayesian models make them ideal tools for public health decision-making. These models allow policymakers to quantify uncertainties, evaluate counterfactual scenarios, and simulate the impact of hypothetical interventions under different urban planning scenarios (Sazzad, 2025; Soomro & Jabbar, 2024). For instance, Bayesian decision analysis can compare the cost-effectiveness of diabetes screening strategies across urban districts or identify optimal locations for community health centers based on posterior risk maps. Bayesian posterior distributions also support the development of risk-based communication strategies that convey not just expected outcomes, but also the credibility of those expectations—an important factor in building trust in health campaigns. These capacities are particularly impactful in urban environments marked by demographic heterogeneity, economic polarization, and political fragmentation—conditions that require adaptive, transparent, and evidence-driven governance (Razzak et al., 2024; Amasiadi et al., 2025; Md et al., 2025). Bayesian models provide probabilistic estimates that can be updated in real-time, accommodating new surveillance data or intervention effects, thereby supporting adaptive public health strategies (Qibria & Hossen, 2023; Masud, Mohammad, & Sazzad, 2023). In essence, Bayesian statistical modeling transforms disease forecasting from a static, retrospective task into a dynamic, prospective decision-support system. This is particularly crucial in the context of T2DM, where early identification of high-risk zones and timely resource allocation can drastically reduce long-term health expenditures and improve population well-being (Masud et al., 2025; Nayla & Haque, 2024; Sanjai et al., 2023; Akter, 2025).

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## LITERATURE REVIEW

The growing urban prevalence of type 2 diabetes mellitus (T2DM) has triggered a surge in quantitative investigations aimed at understanding its etiology, spatial dynamics, and predictive modeling. The literature on diabetes prediction is vast and multidimensional, encompassing clinical, behavioral, demographic, environmental, and infrastructural determinants (Morić et al., 2025). However, traditional epidemiological models often fall short in capturing the uncertainty, heterogeneity, and latent spatial-temporal structures inherent in urban health data. This gap has led to increasing interest in Bayesian statistical models, which provide a flexible probabilistic framework capable of integrating diverse data sources, modeling hierarchical structures, and updating inferences dynamically as new data become available. The scholarly discourse around Bayesian methods for chronic disease modeling—particularly for T2DM—has evolved along several axes: (a) conceptual integration of Bayesian inference into epidemiology, (b) hierarchical and spatial models tailored for urban segmentation, (c) risk factor modeling and latent variable inclusion, (d) model calibration and diagnostics, and (e) public health applications of predictive maps and decision support. The literature further explores innovations such as Bayesian disease mapping, spatial priors (e.g., CAR models), and data fusion techniques, which are particularly useful for modeling T2DM in data-constrained or spatially heterogeneous urban environments (Ahmed et al., 2024). This review systematically synthesizes the key themes, methodological advances, and empirical findings across the intersecting domains of Bayesian modeling and urban diabetes epidemiology. The structure of the review is organized to reflect both the conceptual evolution of Bayesian epidemiology and its practical application to T2DM prediction. Each subsection is developed to provide critical insight into the modeling decisions, data structures, and inferential goals that shape the use of Bayesian models in this domain (Chin‐Yee & Upshur, 2018). Emphasis is placed on studies that not only demonstrate methodological sophistication but also offer empirical validation, public health relevance, and replicable modeling strategies for urban populations.

### Bayesian Inference in Epidemiology

Bayesian inference, grounded in the philosophical notion of probability as a degree of belief, originated with the posthumous publication of Reverend Thomas Bayes' seminal work in 1763, which introduced a rule for updating beliefs based on observed evidence. The subsequent formalization by Pierre-Simon Laplace laid the groundwork for Bayesian probability as a rational framework for reasoning under uncertainty. Historically sidelined by frequentist methodologies due to computational intractability, Bayesian methods began gaining prominence in epidemiology during the late 20th century, especially as computing power expanded and Markov Chain Monte Carlo (MCMC) algorithms became accessible. The philosophical distinction between Bayesian and frequentist approaches rests on the interpretation of probability: while frequentists define probability as long-run relative frequency, Bayesians conceptualize it as a subjective degree of belief updated through Bayes' Theorem (Lovric, 2025; Hossen et al., 2023; Akter & Razzak, 2022).

This epistemological foundation has proven particularly advantageous in public health, where prior knowledge—from expert opinion to historical data—can be explicitly incorporated into the analytical framework. The probabilistic nature of Bayesian reasoning aligns with the intrinsic uncertainties of epidemiological research, including incomplete data, hidden confounders, and the need for small-area estimations. As such, Bayesian inference has found critical application in modeling rare diseases, estimating underreported conditions, and evaluating intervention effectiveness across heterogeneous populations. Its capacity to integrate expert-derived priors with real-world evidence has positioned it as a flexible tool in modern epidemiological science (Wang et al., 2022). Foundationally, Bayesian inference represents a shift from fixed-parameter logic toward dynamic learning, where belief updating reflects the core iterative nature of public health monitoring and risk assessment.

In chronic disease epidemiology, particularly concerning non-communicable diseases like type 2 diabetes, frequentist models such as logistic regression and Cox proportional hazards models have been traditionally utilized for risk estimation and hypothesis testing. These models rely on fixed parameter estimates and confidence intervals derived under the assumption of long-run sampling, which often limits their interpretability and flexibility when dealing with sparse, noisy, or spatially structured health data (Sjölander & Vansteelandt, 2019). In contrast, Bayesian models provide full posterior distributions of parameters, allowing researchers to express results probabilistically—e.g., the probability that the prevalence of diabetes in a neighborhood exceeds a public health threshold.

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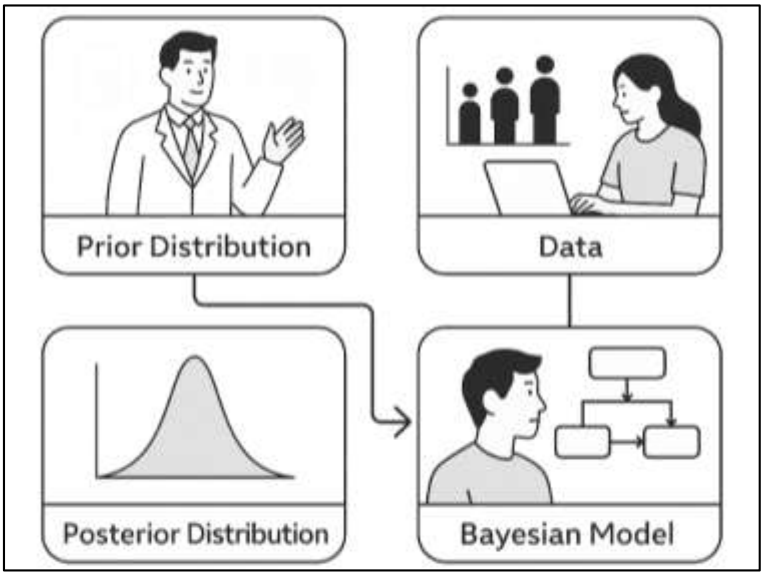
Unlike frequentist confidence intervals, which are often misunderstood as probability statements, Bayesian credible intervals directly quantify uncertainty about parameters given the data. This distinction becomes particularly salient when interpreting the outcomes of policy interventions, where decision-makers require intuitive probabilistic interpretations. Moreover, frequentist models often treat hierarchical or multilevel structures as nuisances to be adjusted, whereas Bayesian hierarchical models are explicitly designed to leverage such structures, borrowing strength across strata to improve precision (Moran & Linden, 2024). This characteristic is especially advantageous in urban diabetes modeling, where city-level data are naturally nested within districts and neighborhoods. Additionally, Bayesian methods are better suited for integrating prior distributions and adapting to small-sample settings, which frequently occur in spatial epidemiology or when analyzing underrepresented subpopulations. Frequentist models, constrained by sample size requirements and rigid assumptions, often struggle with model overfitting or parameter instability in such contexts. Consequently, while both paradigms have methodological merit, Bayesian approaches offer superior versatility and interpretability in chronic disease epidemiology where uncertainty and complexity are the norms (Wang & Jonas, 2021).

**Figure 2: Bayesian Inference in Epidemiological Modeling**




A primary strength of Bayesian inference lies in its capacity for explicit uncertainty quantification, which is a critical consideration in population-level health modeling. Unlike point estimates produced by traditional frequentist models, Bayesian analysis yields full posterior distributions that capture both aleatory and epistemic uncertainty, allowing for more informative decision-making in public health contexts. This probabilistic output enables nuanced interpretations, such as assessing the likelihood that diabetes prevalence exceeds policy thresholds in specific urban subregions. Hierarchical modeling, another hallmark of Bayesian approaches, offers a principled way to incorporate multilevel structure into epidemiological models—e.g., individuals nested within households, neighborhoods, or municipalities. Bayesian hierarchical models allow for the partitioning of variance across levels while enabling partial pooling, thus improving parameter estimation in sparse data environments. This is particularly beneficial in urban studies where small-area estimation and high-resolution mapping of disease burden are vital for resource allocation and intervention design. Additionally, Bayesian frameworks facilitate the incorporation of latent variables, random effects, and contextual moderators into models without violating estimation assumptions—a limitation frequently encountered in generalized linear models (Mun et al., 2021). The flexibility to define prior distributions at each level of a hierarchical structure strengthens model transparency and robustness, especially when integrating expert knowledge or prior empirical findings. For instance, prior studies on the association between air pollution and T2DM can inform priors in urban health models, enhancing predictive power and ecological validity. These methodological advantages make

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Bayesian hierarchical models well-suited for epidemiological investigations marked by heterogeneity, complex dependencies, and data scarcity—hallmarks of chronic disease modeling in urban contexts (Radzvilas et al., 2021).

Bayesian statistical models have increasingly been integrated into population health surveillance systems and chronic disease forecasting frameworks due to their adaptability and data assimilation capabilities. Unlike static modeling techniques, Bayesian models accommodate iterative data integration, making them valuable in surveillance contexts where data are accumulated incrementally or arrive from heterogeneous sources. This dynamic updating capability is particularly relevant for T2DM monitoring in urban populations, where demographic transitions, infrastructural changes, and policy interventions can rapidly alter disease risk landscapes (Frank & Wali, 2021). In disease mapping, Bayesian spatial models allow researchers to generate posterior risk estimates at fine geographic scales while smoothing out noise through spatial priors, such as conditional autoregressive (CAR) structures. These techniques have been successfully employed to visualize undiagnosed diabetes clusters in the U.S., India, and Brazil, helping public health agencies target interventions to underserved or high-risk areas. Additionally, Bayesian forecasting models such as dynamic linear models or Bayesian autoregressive structures have been used to predict future prevalence rates based on historical data and environmental covariates (Sjölander & Vansteelandt, 2019). Bayesian approaches are also instrumental in real-time decision support tools, where ongoing updates to predictions enable timely policy responses. In diabetes screening initiatives, for instance, Bayesian decision analysis has been used to assess the optimal deployment of limited health resources across urban regions with differing risk profiles. Furthermore, the interpretability of Bayesian outputs facilitates their integration into multi-stakeholder public health systems, where intuitive communication of uncertainty is essential (Moran & Linden, 2024). This use of Bayesian inference in surveillance and risk prediction underscores its value in navigating the complex, evolving, and often uncertain terrain of urban epidemiological modeling.

**Bayesian Hierarchical Models for Diabetes Risk Stratification**

Bayesian hierarchical models have become essential tools in stratifying diabetes risk across urban populations by explicitly modeling multi-level structures in which individuals are nested within broader spatial units such as neighborhoods, census tracts, or metropolitan zones. These models accommodate the complex interplay of individual-level and contextual-level factors that drive type 2 diabetes mellitus (T2DM) disparities in urban settings (Mun et al., 2021). Individual risk factors such as body mass index (BMI), dietary habits, physical inactivity, and family history interact with neighborhood-level determinants like walkability, food deserts, pollution levels, and healthcare access. Bayesian multilevel models allow researchers to jointly analyze these layers while quantifying the contribution of each level to overall disease risk (Radzvilas et al., 2021). The nested data structure is particularly relevant in large-scale diabetes surveillance programs, such as those implemented in New York City, São Paulo, or Delhi, where individual-level health survey data are routinely collected alongside urban planning, socio-demographic, and environmental datasets. Hierarchical modeling permits partial pooling, which improves parameter estimation for small subgroups by borrowing strength from the broader population distribution. This is especially advantageous in stratifying diabetes risk among socioeconomically marginalized groups whose data may be underrepresented or noisy (Boumendil et al., 2024). Studies from the U.S. and U.K. have used multilevel Bayesian approaches to show that area-level deprivation indices and ethnic clustering significantly modify the individual risk of diabetes, reinforcing the need for models that capture nested health determinants.

Incorporating random effects into Bayesian hierarchical models enables researchers to address unobserved heterogeneity that may arise from area-level influences, healthcare system variations, or latent spatial structures in urban settings. Random intercepts and slopes are used to capture variability across geographic units without assuming independence, a common limitation in traditional fixed-effects models (Frank & Wali, 2021). These random effects help explain overdispersion and clustering of T2DM prevalence beyond what can be attributed to measured covariates. For example, diabetes prevalence in one urban district may differ significantly from another due to unmeasured cultural, environmental, or infrastructural factors. Introducing area-level random effects accounts for this uncertainty and enhances the credibility of posterior estimates (Fang et al., 2019). In addition to random effects, latent variables are increasingly employed to model complex relationships in Bayesian epidemiology. Latent constructs such as "neighborhood social capital," "urban stress," or "environmental toxicity" often manifest indirectly through multiple observed indicators, and their inclusion improves model fit and explanatory power. For instance, Su et al. (2020) used latent constructs to model unmeasured spatial confounding in urban diabetes studies, while Stallard et al. (2020) introduced latent community-level lifestyle indicators to improve the predictive capacity of geostatistical models. Such innovations reduce residual confounding, especially in high-dimensional settings, and are particularly valuable when studying inner-city areas with multiple overlapping vulnerabilities. Applications of these latent and random effect structures have been demonstrated in predictive modeling of T2DM across varied urban contexts—from city-wide health assessments in Seoul to neighborhood-level surveillance in London (Hundscheid et al., 2024) and district-wise modeling in Indian metros. These implementations underscore the ability of Bayesian hierarchical models to embed complex and unobserved health dynamics into statistically robust structures without oversimplifying the problem space.

Urban environments are intrinsically heterogeneous, featuring diverse ethnic populations, variable infrastructure, unequal healthcare access, and socio-economic stratification—all of which affect diabetes risk profiles. Bayesian hierarchical models are well-suited to capture this heterogeneity by allowing varying intercepts and slopes across spatial clusters, enhancing sensitivity to contextual influences that vary by locality. For instance, studies in the United States have shown that urban clusters with predominantly minority populations or low-income households exhibit higher T2DM risk even after adjusting for individual behaviors. Bayesian modeling frameworks quantify this variability using structured and unstructured random effects, facilitating nuanced estimations at multiple geographic resolutions (Wang et al., 2024). Moreover, these models incorporate both spatially structured priors—such as conditional autoregressive (CAR) models—and unstructured noise components, allowing analysts to disentangle systematic spatial trends from stochastic variation. This dual capacity is critical in urban epidemiology, where social and environmental gradients do not necessarily follow linear or contiguous patterns. For example, Wang et al. (2022) demonstrated the use of structured priors to identify urban heat islands associated with increased diabetes prevalence in China, while Booth et al. (2024) modeled zip-code level heterogeneity in U.S. metropolitan regions. Bayesian models also outperform traditional frequentist models when local sample sizes are small or when urban clusters exhibit extreme values, thanks to the mechanism of shrinkage through hierarchical priors. This improves estimation accuracy in underserved or marginalized districts, where health disparities are most pronounced. Consequently, these models not only accommodate but actively leverage heterogeneity, making them indispensable for stratified public health surveillance and for identifying localized patterns of diabetes risk (Ursino & Stallard, 2021).

**Spatial Bayesian Models for Urban Diabetes Mapping**

Spatial Bayesian models have emerged as a robust methodological framework in epidemiological mapping, particularly for chronic diseases like type 2 diabetes mellitus (T2DM) in urban settings. Two widely adopted approaches are Conditional Autoregressive (CAR) models and Gaussian Markov Random Fields (GMRFs), both of which are designed to account for spatial autocorrelation and structure in area-level health data (Besag et al., 1991; Banerjee et al., 2004). CAR models represent the spatial dependencies of disease risk using neighborhood structures—defining how each region's estimate is conditionally dependent on its neighbors—while GMRFs approximate spatial random effects using sparse precision matrices for computational efficiency (Ruiz-Alejos et al., 2018). These models are particularly advantageous in urban epidemiology, where diabetes prevalence is often clustered spatially due to shared environmental, socioeconomic, and infrastructural characteristics. The utility of CAR models in diabetes mapping has been demonstrated in a range of studies, including Dugani et al. (2021), who illustrated how structured priors improve estimation stability in regions with sparse data. GMRFs have further enabled scalable modeling of high-resolution urban spaces, as seen in Banasiak et al. (2020) through the Integrated Nested Laplace Approximation (INLA) framework, facilitating faster estimation without compromising accuracy. These models also accommodate unstructured random effects, thereby allowing analysts to capture both structured (spatially dependent) and unstructured (independent) components of variation. Such modeling strategies have shown effectiveness in complex urban settings with irregular boundaries, such as New York City and London, where neighborhood-level clustering of diabetes prevalence is evident (Dendup et al., 2018). The application of CAR and GMRF structures within a Bayesian context provides a principled solution for accounting for spatial correlation, improving both estimation precision and interpretability in disease risk mapping.

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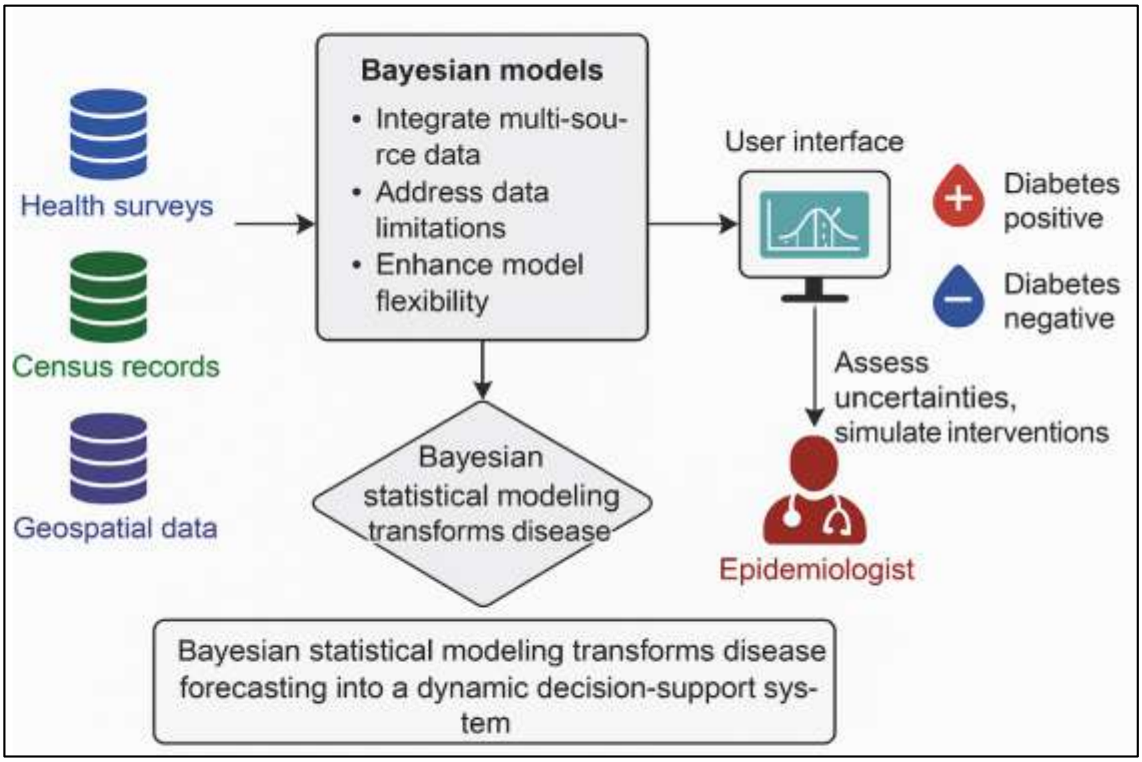
**Figure: Bayesian Urban Diabetes Prediction Framework**




Bayesian spatial models derive much of their inferential strength from the use of adjacency matrices and spatial priors that formally encode the neighborhood structure of geographic units. Adjacency matrices define which spatial units are considered neighbors, typically based on shared borders or proximity, and serve as the backbone for CAR and GMRF models. Spatial priors, particularly intrinsic CAR priors, impose smoothing constraints such that geographically proximate areas are assumed to have similar disease risks, thereby reducing noise and enhancing estimation robustness in small-area settings (Motala et al., 2022). These tools are particularly crucial in urban diabetes research, where administrative units such as census tracts, wards, or zip codes exhibit varying data completeness and sample sizes. The integration of adjacency structures into Bayesian models has allowed public health researchers to capture localized spatial dependence in T2DM prevalence across urban geographies. Studies by Iezadi et al. (2024) demonstrate how spatial smoothing derived from adjacency matrices enhances predictive performance and reveals spatial gradients of risk. For example, Xue-Juan et al. (2018) used adjacency-informed priors to assess spatial clusters of T2DM in Beijing, identifying high-risk zones shaped by air pollution and access to healthcare. Similarly, De la Fuente et al. (2021) applied adjacency-based Bayesian models to examine inner-city London diabetes rates, finding elevated risk concentrated in immigrant-dense neighborhoods with limited food access and walkability. Adjacency matrices also facilitate incorporation of spatial heterogeneity into hierarchical models, enabling separation of global versus local effects in multilevel urban frameworks. Such spatial priors, when appropriately specified, allow for "borrowing strength" from adjacent regions to stabilize estimates in areas with sparse data, making them essential tools in small-area diabetes surveillance (Wiki et al., 2021). These approaches ensure that spatial structure is not treated as statistical noise but as a critical determinant of observed health patterns in urban settings.

Bayesian spatial models have been instrumental in generating high-resolution diabetes hotspot maps, revealing critical patterns of disease clustering at the urban scale. By leveraging area-level covariates and spatial priors, these models yield smoothed prevalence estimates that highlight neighborhoods with elevated risk while accounting for sampling variability and spatial autocorrelation. This approach has enabled urban health departments to identify not only zones of concern but also potential environmental and socio-demographic correlates of disease burden. In New York City, for example, Zhang et al. (2024) employed Bayesian mapping techniques using zip-

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code level data to identify high-diabetes-prevalence neighborhoods concentrated in the Bronx and East Brooklyn, aligning with food insecurity and ethnic composition. Similarly, Shetty et al. (2021) utilized spatial Bayesian modeling to examine how walkability scores, access to parks, and public transportation proximity influenced the spatial distribution of T2DM in Los Angeles County. In London, Zheng et al. (2018) demonstrated how social housing density and public health resource allocation aligned with mapped diabetes hotspots in inner-city boroughs. These studies exemplify how area-level spatial models go beyond disease estimation by integrating urban contextual data—such as housing conditions, pollution levels, or healthcare access—into inferential frameworks. The mapping of such spatial risk gradients is crucial for visual epidemiology, wherein policy-makers and public health officials utilize disease maps for evidence-based resource deployment and intervention targeting. Bayesian maps generated from structured spatial models often reveal hidden spatial clusters not easily detectable through traditional epidemiological statistics. The capacity to model uncertainty at the spatial level further enhances the interpretability of hotspot visualizations, aiding in the development of tailored public health responses that consider not only where diabetes is most prevalent but also the reliability of those estimates (Farhane et al., 2021).

Several empirical case studies from around the world demonstrate the versatility of Bayesian spatial models in capturing the urban distribution of type 2 diabetes. In the United States, numerous studies have applied spatial Bayesian frameworks to assess prevalence patterns at the county and zip-code levels. Amuda and Berkowitz (2019) used CAR-based disease mapping to reveal high-risk urban zones in New York, Chicago, and Los Angeles, associating diabetes clusters with racial segregation and economic disadvantage. In India, Jeffrey et al. (2019) employed hierarchical Bayesian models to map diabetes prevalence across Indian metro districts, identifying stark disparities between low-income and affluent wards within cities like Mumbai and Delhi. In China, Wang et al. (2019) applied a spatial Bayesian model incorporating air quality, urban heat indices, and land-use data to estimate diabetes risk across neighborhoods in Beijing, showing environmental exposures as critical spatial determinants. Taderegew et al. (2020) conducted a similar study in South Korea, integrating pollution, green space, and socio-demographic data using Bayesian GMRFs to create city-wide diabetes prevalence maps in Seoul. These urban models have been central to municipal public health planning, especially in contexts of rapid urbanization and environmental transition. In Brazil, utilized Bayesian geostatistical modeling to estimate community-level diabetes prevalence in São Paulo, using spatial smoothing to detect peri-urban clusters linked to food deserts and poor access to clinics. From sub-Saharan Africa, Bigna et al. (2021) and Mutua et al. (2020) adapted spatial Bayesian models to map diabetes risk in Nairobi and Lagos, respectively, where urban informality and infrastructure gaps required robust estimation methods that could handle missing data and latent variation. These global case studies underscore the adaptability of Bayesian spatial modeling across diverse urban contexts, affirming its centrality in understanding the geospatial epidemiology of diabetes in both high- and low-resource settings (Lawson, 2013; Congdon, 2014; Rue et al., 2009).

**Temporal and Spatio-Temporal Bayesian Models**

Dynamic Bayesian models (DBMs) have become pivotal in the longitudinal analysis of chronic disease trends, including type 2 diabetes mellitus (T2DM), by accommodating time-dependent fluctuations and enabling probabilistic temporal forecasting. These models treat time as an evolving state within a probabilistic framework, thereby capturing the changing prevalence of T2DM in response to socioeconomic, behavioral, and environmental dynamics (Shiguihara et al., 2021). Dynamic linear models (DLMs), one of the foundational structures within DBMs, allow parameters to evolve over time by modeling latent states as stochastic processes, thereby refining disease risk prediction as new data accumulate. In diabetes epidemiology, DBMs have been utilized to forecast changes in urban prevalence due to policy interventions, infrastructural transformations, or demographic shifts. For instance, Wang et al. (2019) applied DLMs to state-level diabetes data in the U.S., showing how urbanization trajectories influenced yearly risk updates. Similarly, Dang et al. (2025) demonstrated how temporal smoothing in Bayesian models improved estimation of diabetes trends in urbanized Scottish districts. These methods accommodate autocorrelation in both observed outcomes and covariates across time, thereby capturing trends often missed by static models. Studies by Zeng et al. (2022) formalized spatio-temporal dynamic models with integrated spatial and temporal components, setting a benchmark for trend forecasting in epidemiological mapping. Their frameworks have been further refined through the use of Integrated Nested Laplace Approximation (INLA), which enhances computational efficiency in fitting time-evolving spatial models. Bayesian

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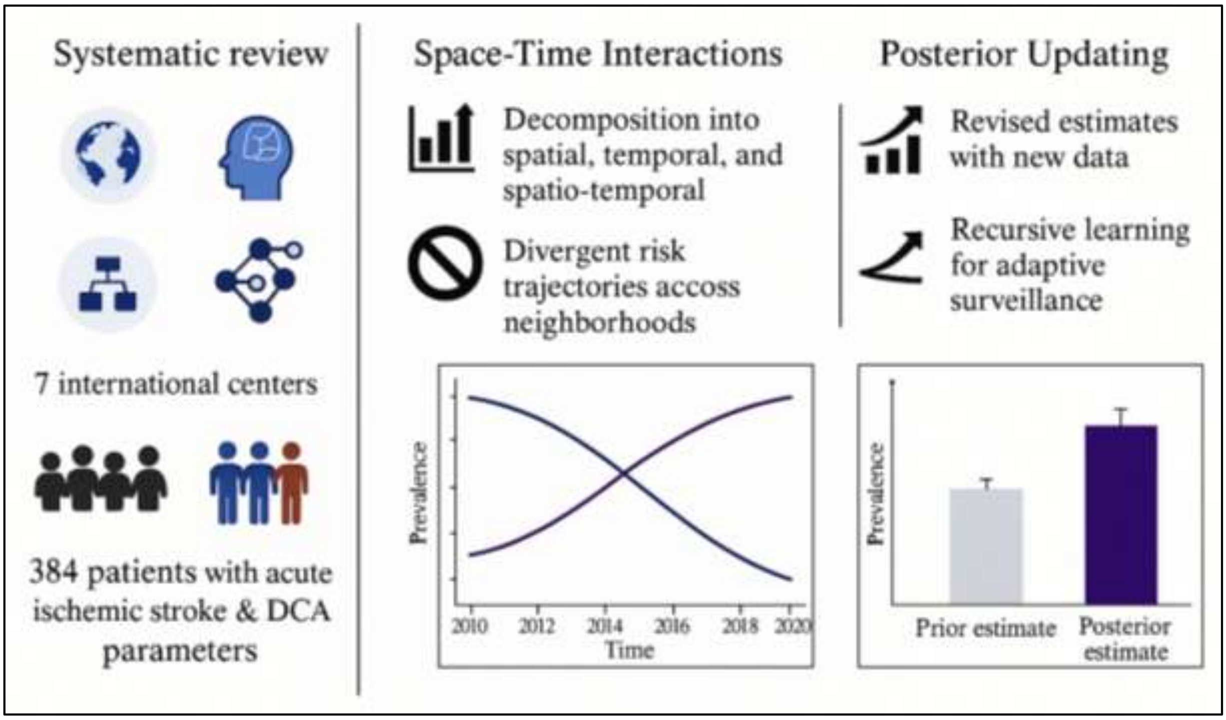
dynamic modeling has also been applied in urban disease surveillance systems in countries like China, Brazil, and India, allowing analysts to capture urban diabetes progression over years with robust inferential support.

**Figure 3: Dynamic Bayesian Models for Diabetes Trends**




The integration of space-time interaction terms within Bayesian hierarchical models significantly enhances the capacity to disentangle the joint effects of geography and temporal progression on T2DM prevalence. Such models allow for the decomposition of variance into spatial, temporal, and spatio-temporal interaction components, enabling nuanced exploration of how diabetes risk evolves across both space and time. Space-time interactions are particularly relevant in urban studies, where neighborhoods may experience divergent temporal trends due to policy interventions, migration, or environmental change (Precup et al., 2022). For example, Lamb et al., (2020) applied space-time interaction models to cancer incidence in Italy, demonstrating patterns of localized surges in disease rates. Their methodology has since been adapted in T2DM modeling, including studies in Latin America and South Asia, where neighborhood-specific temporal effects reveal divergent trajectories of disease risk. Cheng, Gill, Zhang, et al. (2018) expanded this framework by introducing random effects for interactions, allowing better shrinkage and borrowing of strength across both time points and spatial units. In Bayesian spatio-temporal models, the interaction terms often include structured components (e.g., spatial autocorrelation captured by CAR priors) and unstructured noise (e.g., random fluctuations over time), which together allow models to reflect both persistent and transient trends. Zhang et al. (2018) utilized such a structure in U.S. urban counties, revealing how some neighborhoods exhibited sustained high diabetes prevalence, while others experienced temporary spikes aligned with economic shocks or food policy changes. The framework developed by Cheng, Gill, Ensch, et al. (2018) further advanced this modeling by employing INLA-based estimation for temporally indexed neighborhood data. These models enable epidemiologists to capture joint variance patterns, where geography and time reinforce or offset each other in shaping T2DM risks. This complexity cannot be fully accounted for by additive models, underscoring the relevance of hierarchical structures with rich interaction terms in understanding urban diabetes epidemiology (Han et al., 2018).

A core feature of Bayesian inference is posterior updating, which makes it inherently well-suited for epidemiological settings where real-time data and longitudinal monitoring are essential. As new data become available, posterior distributions from prior time points are updated, allowing revised estimations of diabetes prevalence without restarting the analytical process. This process is particularly powerful in public health surveillance systems where urban populations are monitored continuously, and prevalence estimations must be responsive to changing conditions (Zhang et al., 2021). Posterior updating provides a formal mechanism for adaptive learning, in which prior estimates are dynamically revised to incorporate new surveillance inputs such as electronic health records (EHRs), biomarker screenings, or social determinant data. Millar et al. (2021) highlight how Bayesian methods enable recursive updating in hierarchical models, improving precision for subpopulations with limited baseline data. In T2DM surveillance, Deng et al. (2018) showed how sequential updating of community-level estimates in California enhanced policy response timing and resource targeting. Duerr et al. (2018) demonstrated posterior updating in city-level diabetes models in Europe and China, respectively, using temporally stratified data to revise neighborhood risk estimates annually. This technique has also been employed in sub-Saharan Africa, where frequent data reporting from health facilities allows for near-continuous Bayesian recalibration of disease prevalence. INLA and MCMC frameworks facilitate this updating in both fully Bayesian and approximate Bayesian settings, balancing computational speed with model complexity (Osipov & Osipova, 2018). These iterative processes offer the dual advantage of maintaining model accuracy over time and reducing overreliance on outdated priors. Posterior updating has thus proven indispensable in longitudinal disease surveillance systems where predictive fidelity must be preserved across rapidly shifting urban contexts (Li et al., 2020).

**Bayesian Integration of Multi-Source**

Bayesian frameworks excel in integrating diverse datasets such as health surveys, electronic health records (EHRs), satellite imagery, and census data—each offering unique dimensions for modeling type 2 diabetes mellitus (T2DM) in urban contexts. Survey data provide self-reported behavioral and lifestyle variables, while EHRs contribute clinically validated diagnostics and treatment histories. Satellite imagery supplies spatial and environmental variables, including land use, greenness indices, and pollution exposure, which influence metabolic health outcomes. Census data add demographic, socioeconomic, and infrastructural context, enabling small-area estimation for underrepresented neighborhoods (Yu et al., 2019).

Bayesian models allow these heterogeneous data sources to be merged within a single inferential structure, accommodating differences in scale, measurement error, and temporal resolution. For example, Yenduri et al. (2022) integrated neighborhood-level EHRs with census tract characteristics in Los Angeles to model diabetes prevalence using hierarchical Bayesian approaches. Similarly, Nazia et al. (2022) combined survey data from the Behavioral Risk Factor Surveillance System (BRFSS) with zip-code level demographic data to refine prevalence estimates in urban U.S. counties. In Brazil, Wang et al. (2021) fused satellite-derived walkability scores with local health records to predict diabetes distribution in São Paulo. The flexibility of Bayesian methods in handling data from varying sources stems from their probabilistic architecture, which allows the specification of likelihoods for each dataset and hierarchical modeling to unify them at different levels. This feature is particularly advantageous in urban epidemiology, where data silos and incompatible formats are common (Xu et al., 2018). Integrating survey, EHR, satellite, and census data using Bayesian models leads to richer and more accurate spatial inferences about diabetes burden across complex urban environments. Missing data present a pervasive challenge in epidemiological research, especially in urban health surveillance, where data fragmentation is exacerbated by differences in reporting systems, administrative boundaries, and healthcare access. Bayesian imputation offers a rigorous solution to this issue by treating missing values as additional parameters in the model, drawing from the posterior distribution to estimate them conditionally based on observed data (Qian & Zhao, 2018). This approach enables uncertainty around the imputed values to be propagated through the entire inferential process, improving model robustness and avoiding biased conclusions. Bayesian multiple imputation has been applied in studies involving both individual-level and ecological data. For example, Li et al. (2019) utilized Bayesian techniques to address covariate missingness in longitudinal health datasets. Fang et al. (2015) implemented a hierarchical Bayesian model to impute missing demographic indicators in BRFSS data before estimating county-level diabetes prevalence. Similarly, Purwanto et al. (2021) imputed missing socioeconomic indicators in Indian urban districts to enable full Bayesian modeling of T2DM trends. These efforts demonstrate the adaptability of Bayesian methods across diverse health and spatial contexts. Bayesian data augmentation techniques are particularly beneficial in small-area estimation, where sample sizes are often insufficient for direct

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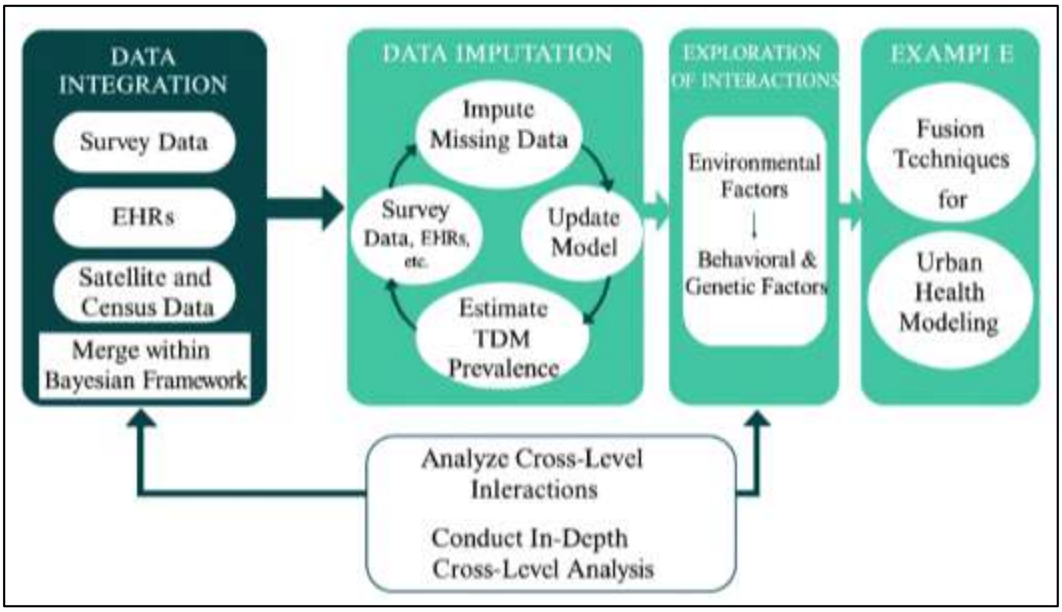
estimation. Using hierarchical priors and latent variable structures, these models borrow strength from neighboring or higher-level regions to inform imputation. Zhao et al. (2019) demonstrated how integrated spatial smoothing could enhance the imputation of spatially structured missing data in health surveys. In sub-Saharan Africa, Li et al. (2018) applied Bayesian imputation to incomplete health records in Lagos and Nairobi, compensating for gaps due to underreporting and variable data collection protocols. This capacity for probabilistic treatment of missing data sets Bayesian models apart from traditional deterministic approaches, which often rely on mean substitution or deletion, leading to bias and loss of precision. Bayesian imputation provides a statistically principled mechanism for preserving data integrity in complex urban epidemiological datasets (Droin et al., 2021).

**Figure 4: Bayesian Framework for Urban Diabetes**




Bayesian hierarchical models are uniquely positioned to model cross-level interactions involving environmental, behavioral, and genetic risk factors for T2DM in urban populations. These interactions are critical in capturing how macro-level urban exposures modulate individual-level susceptibility to metabolic disorders (Yang et al., 2018). For instance, the impact of walkability or pollution exposure on T2DM may vary depending on individual behavioral profiles such as exercise frequency, diet, or genetic predisposition. Traditional models struggle to accommodate these interactions due to complexity and multicollinearity, whereas Bayesian models use hierarchical priors to stabilize estimates and permit partial pooling. Studies incorporating environmental-behavioral interactions within Bayesian frameworks include (Zhang et al., 2020), who showed how local green space modified the effect of physical inactivity on diabetes risk. Similarly, Hu and Downs (2019) modeled the interaction between air quality and BMI in Seoul, demonstrating the spatially varying impact of pollution across different population subgroups. Sartorius et al. (2021) extended this approach in Beijing by linking remote-sensing data on urban heat islands with individual-level dietary patterns, identifying higher T2DM risks in low-income neighborhoods with poor access to cooling infrastructure. In terms of genetic interactions, Bayesian models have been used to assess how known polymorphisms (e.g., TCF7L2, FTO) interact with environmental exposures. Ghosh et al. (2016) incorporated genetic scores into a Bayesian model alongside air quality and food security data in urban India, enhancing prediction accuracy. In the U.S., Li et al. (2021) modeled the interplay of race, healthcare access, and obesity as hierarchical predictors, identifying significant urban-rural divergences in T2DM risks. These models allow cross-level terms to be incorporated without sacrificing parsimony or interpretability, thanks to shrinkage effects and hierarchical structure. Their strength lies in acknowledging and quantifying the multiscale mechanisms that drive diabetes heterogeneity in urban settings (Amasiadi et al., 2025).

Bayesian data fusion techniques have been widely applied in urban health modeling to combine disparate datasets into a coherent inferential structure, thereby improving diabetes prediction and spatial precision. These models allow integration of both structured and unstructured data types—such as administrative records, sensor data, and population surveys—within multilevel spatial-temporal hierarchies. In Rostamzadeh et al. (2021) merged walkability metrics from satellite imagery, public clinic records, and population census data to model diabetes hotspots using Bayesian hierarchical smoothing. In New York City, Goyal and Mahmoud (2024) combined BRFSS data with EHRs and environmental indices to refine zip-code-level prevalence maps. In India, fusion modeling to integrate district-level surveillance data, remote sensing data on green coverage, and household wealth indices in estimating diabetes risk in metropolitan cities. Similarly, Bayesian data fusion to analyze multiple spatial scales in London, incorporating primary care statistics, ethnicity distributions, and housing density. These examples highlight the model's utility in harmonizing datasets with different levels of spatial aggregation, temporal frequency, and data quality. Fusion models also enable synergistic use of expert-derived priors and machine-generated covariates. For instance, Kumar et al.(2024) incorporated domain-specific priors on pollution-diabetes links with machine-learning-derived traffic indices in Seoul. In sub-Saharan Africa, Taha (2025) applied fusion techniques to combine traditional clinic-based monitoring with geotagged mobile health data for urban diabetes surveillance. This flexibility allows Bayesian models to serve as integrative platforms for synthesizing modern and legacy data, even when they differ significantly in resolution and format. These studies underscore that data fusion, facilitated by Bayesian methods, enhances the scope, depth, and reliability of urban diabetes modeling by leveraging the strengths of diverse data sources while accounting for their respective uncertainties and limitations.

**Computational Approaches**

Bayesian statistical estimation relies heavily on computational algorithms capable of approximating complex posterior distributions. Among these, Markov Chain Monte Carlo (MCMC) methods have long served as the gold standard in Bayesian computation, offering precise estimation through iterative sampling. MCMC algorithms such as Gibbs sampling and the Metropolis-Hastings algorithm are particularly suited for hierarchical and high-dimensional models often used in urban diabetes research. For example, Sella et al. (2025) employed Gibbs sampling in a hierarchical model of diabetes prevalence using census and survey data in Los Angeles, while Xu et al. (2023) used Metropolis-Hastings algorithms for spatial modeling of health disparities across Georgia counties. Despite MCMC's flexibility, its computational burden has motivated alternatives like the Integrated Nested Laplace Approximation (INLA), which provides fast, accurate approximations for latent Gaussian models, especially in spatial and spatio-temporal settings.

INLA has been widely used for urban disease mapping, such as in Algarvio et al. (2025), where city-level diabetes prevalence in India was modeled using hierarchical spatial priors. Similarly, Marques et al. (2024) applied INLA to integrate satellite imagery with clinical data in Beijing, enhancing computational speed without compromising model complexity. Variational inference (VI) offers yet another approach by converting posterior inference into an optimization problem. Though less common in epidemiology, it has been used to scale Bayesian neural networks and handle large urban datasets with sparse labels. VI techniques have shown utility in health studies involving streaming or sensor-based urban data. These alternatives to traditional MCMC demonstrate the evolution of Bayesian computational tools, each suited for different levels of model complexity and dataset size in urban diabetes modeling (Berge et al., 2023). Ensuring the validity of Bayesian model results necessitates rigorous convergence diagnostics and posterior predictive checks, especially when employing MCMC or other sampling-based estimation methods. Convergence diagnostics assess whether the Markov chains have sufficiently explored the posterior distribution, with commonly used tools including the Gelman-Rubin statistic ($\hat{R}$), trace plots, and autocorrelation diagnostics. These metrics are essential in urban diabetes models involving complex spatial hierarchies or latent structures, where posterior landscapes may exhibit multimodality or slow mixing. Studies such as Sim et al. (2024) applied convergence diagnostics in Bayesian spatial models for small-area diabetes estimation in the UK, verifying chain stabilization using multiple chains and convergence plots.

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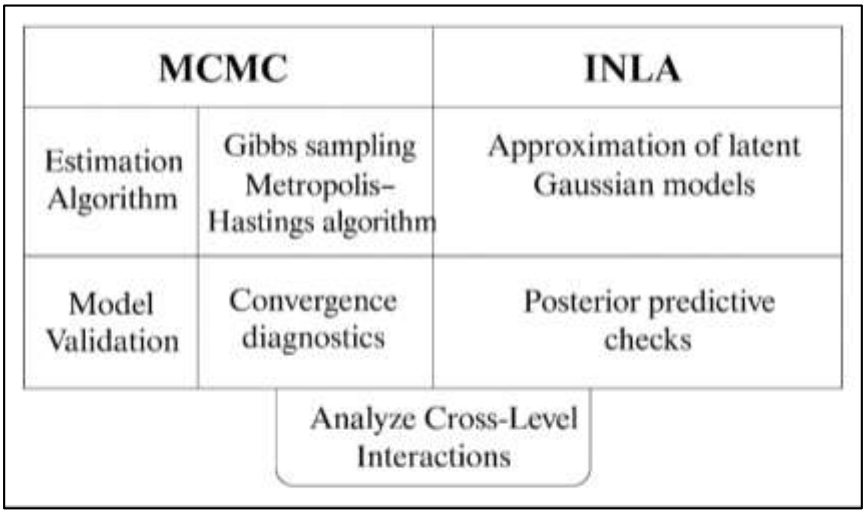
**Figure 5: Bayesian Statistical Methods**




Similarly, Benhamza et al. (2025) emphasized the use of Monte Carlo error estimation in checking the reliability of posterior summaries. In INLA-based models, diagnostic tools differ since approximation replaces sampling; model fit is commonly assessed using the deviance information criterion (DIC), conditional predictive ordinate (CPO), and marginal likelihoods. Posterior predictive checks (PPCs) offer an additional validation layer by comparing observed data with replicated datasets drawn from the posterior distribution. This method allows for graphical and quantitative assessment of model adequacy. Sirocchi et al. (2024) used PPCs to evaluate diabetes risk models at the zip-code level in New York, identifying discrepancies between predicted and observed prevalence in immigrant-dense regions. Similarly, Alzakari et al. (2024) employed PPCs to test predictive accuracy in Beijing's spatial diabetes model, examining residual patterns across urban districts. These diagnostic protocols not only safeguard against overfitting but also improve interpretability, especially when model outputs are communicated to non-technical stakeholders in public health and urban governance (Chen et al., 2024). Their consistent application is integral to maintaining the statistical integrity of Bayesian disease mapping.

**Predictive Performance and Public Health Applications**

Bayesian models distinguish themselves through their ability to generate posterior predictive distributions, offering not only point estimates but full distributions of likely outcomes. This property enhances probabilistic forecasting, a critical feature in public health where uncertainty must be explicitly conveyed (Adar & Md, 2023; Steyaert et al., 2023). In contrast to traditional methods that provide single-value predictions, Bayesian models estimate a full range of plausible prevalence or incidence values, conditional on prior beliefs and observed data. These distributions allow public health professionals to assess risk probabilities, credibility intervals, and uncertainty bounds with statistical rigor. Applications in urban diabetes research demonstrate the utility of these outputs in risk forecasting. Clark et al. (2025) used posterior predictive distributions to produce probabilistic maps of undiagnosed diabetes prevalence across urban neighborhoods in the U.S., allowing nuanced interpretation of high-risk zones.  applied similar approaches in Indian cities, generating interval estimates of district-level prevalence with probabilistic confidence bounds. These distributions also enable prediction intervals for time-series models, capturing likely future trends under data-informed uncertainty. Goyal and Mahmoud (2024) highlighted how posterior predictive simulations were used to validate diabetes forecasts in Milan, ensuring model realism under varying spatial and temporal inputs. In Seoul, Abbas et al. (2024) employed posterior predictive checks to assess how pollution exposure interacted with urban form in determining diabetes incidence. The reliability and interpretability of these forecasts are further supported by techniques such as posterior predictive loss criteria, Bayesian p-values, and comparison with observed test datasets (Islam & Debashish, 2025; Polotskaya et al., 2024). These probabilistic outputs provide a more comprehensive understanding of urban diabetes risk than traditional deterministic models, ensuring transparent and statistically grounded public health communication.

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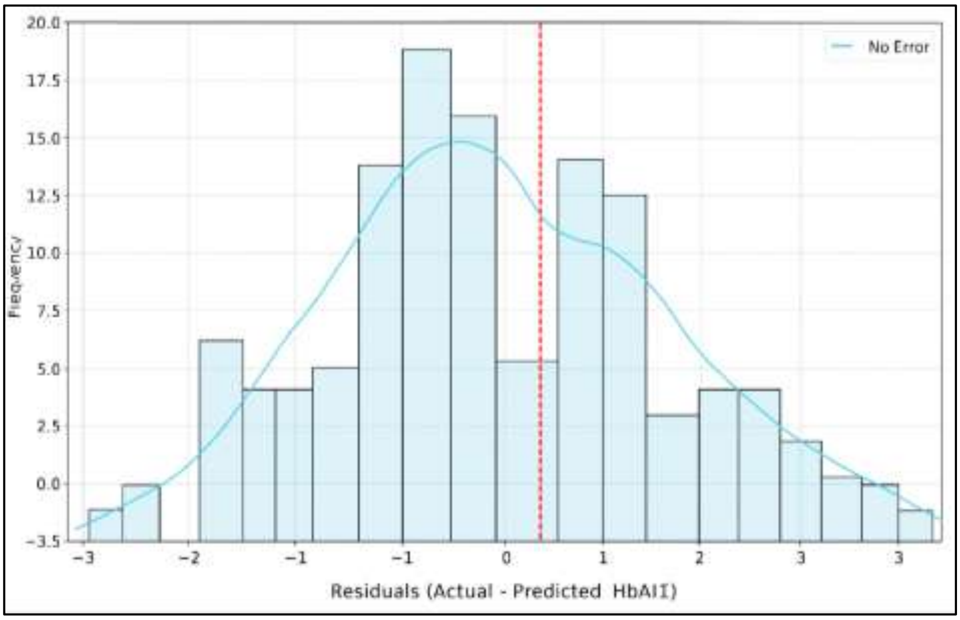
**Figure 6: Distribution of Residuals for BNN Predictions**




Bayesian decision theory integrates posterior probability distributions with utility functions to inform optimal choices under uncertainty, providing a robust foundation for public health policy evaluation (Liu & Liao, 2024; Islam & Ishtiaque, 2025). This framework evaluates the expected outcomes of competing interventions—such as diabetes screening, public awareness campaigns, or zoning reform—by combining statistical inference with decision-making criteria. Decision analysis incorporates cost, benefit, and probabilistic health outcomes into a coherent modeling architecture, allowing policymakers to compare intervention strategies based on their expected utility. In urban diabetes research, Bayesian decision models have been applied to determine optimal resource allocation across city districts with unequal risk profiles. Ngartera et al. (2024) used a Bayesian utility function to prioritize interventions in underserved neighborhoods in Los Angeles based on probabilistic health outcomes and demographic vulnerability. Similarly, Pagano et al. (2018) employed Bayesian decision frameworks to rank small-area intervention zones in England by integrating posterior diabetes risk estimates with health cost data. Wang et al.,(2023) incorporated decision theory into diabetes forecasting in Seoul, modeling the tradeoffs between green infrastructure investment and expected T2DM reductions. Li et al. (2023) emphasized that decision-theoretic approaches enhance interpretability by explicitly connecting statistical inference with public policy consequences. Cure et al. (2024) employed a decision model to evaluate the policy relevance of posterior distributions in the Indian noncommunicable disease surveillance system. In Brazil, Lu et al. (2024) used Bayesian utility analysis to prioritize mobile health clinics based on neighborhood-level diabetes prevalence and service accessibility. These implementations demonstrate how Bayesian decision theory enhances analytical transparency and supports public health governance by framing predictions within an actionable, utility-based structure (Janmontree et al., 2025; Subrato, 2025).

Bayesian approaches have proven indispensable in cost-effectiveness analysis (CEA) of diabetes screening programs, offering a framework for integrating uncertainty, hierarchical data, and economic evaluation in a single analytical structure. Bayesian CEAs allow for the simultaneous modeling of clinical outcomes, economic costs, and intervention utilities while accounting for variability across urban subpopulations. They produce posterior distributions for cost-effectiveness ratios, enabling probabilistic statements about whether an intervention is economically justified under different willingness-to-pay thresholds (Nogueira et al., 2023; Subrato & Faria, 2025). Studies evaluating urban diabetes screening strategies have leveraged Bayesian CEA frameworks to accommodate stratified risk, budget constraints, and urban infrastructural differences. For example, Marcot and Penman (2019) conducted a cost-effectiveness comparison of zip-code targeted versus city-wide screening in U.S. cities, showing that spatial targeting yielded higher expected utility at lower cost. Goswami et al. (2023) performed a Bayesian economic evaluation of screening modalities in Delhi's informal settlements, incorporating prior information on service uptake and diagnostic sensitivity. Dziak (2018b) similarly modeled expected savings from early detection campaigns in Los Angeles using hierarchical cost models informed by EHR and census data. Panagoulias et al. (2024) emphasized that Bayesian CEAs are particularly useful in cases of parameter uncertainty, such as unknown compliance rates or uncertain long-term outcomes, by allowing posterior distributions to be carried through all economic outputs. Dziak (2018a) incorporated environmental risk exposure into their screening CEA in Seoul, refining estimates of avoided healthcare costs based on air pollution mitigation. Bayesian cost-effectiveness models provide a rigorous foundation for assessing not only clinical impact but also financial feasibility, thereby aligning public health policy with fiscal responsibility (Kistamás et al., 2024; Subrato & Md, 2024).

Bayesian models generate outputs that are not only analytically rigorous but also highly adaptable to visualization and decision support platforms, facilitating data-driven decisions by urban health authorities. Posterior estimates, predictive intervals, and spatial risk gradients can be rendered as interactive maps, dashboards, and uncertainty plots, enabling public health professionals to grasp complex epidemiological dynamics at a glance (Feliciano Jr; Akter, 2025). Visual epidemiology relies on translating statistical findings into accessible and policy-relevant formats—an area where Bayesian tools excel due to their probabilistic nature and compatibility with geospatial visualization frameworks (Shaiful & Akter, 2025). In New York City, Plenary (2020) implemented a Bayesian disease mapping interface that displays zip-code level diabetes prevalence along with uncertainty bands, aiding in targeted public health outreach. Chinnaswamy et al, (2019) created district-level dashboards using INLA-derived predictions in India's National Urban Health Mission, supporting the coordination of mobile diabetes screening units. In São Paulo, Pettit et al. (2018) combined R-INLA with GIS mapping to provide decision-makers with real-time spatial visualizations of diabetes hotspots layered with access to health infrastructure. Keenan and Jankowski (2019) demonstrated how INLA-based model outputs can be integrated into public health surveillance systems, allowing for dynamic updating and visualization of urban disease trends. Wu et al. (2020) used web-based mapping tools to present Bayesian predictions of diabetes risk to Los Angeles County health departments, incorporating layers for demographics, clinics, and socioeconomic status. Posterior predictive uncertainty ribbons and spatial heatmaps produced by these models enhance transparency and contextual interpretation. These visual outputs have been used in participatory health planning, stakeholder engagement, and real-time program monitoring. They provide health departments with intuitive, interactive formats for interpreting complex outputs and tailoring interventions accordingly, reinforcing the integration of Bayesian analytics into real-world urban governance frameworks (Khan et al., 2025; Akter & Shaiful, 2024).

**Bayesian Models vs. Machine Learning**

Bayesian models and machine learning (ML) techniques differ fundamentally in their balance between interpretability and predictive performance, a distinction that significantly influences their application in urban diabetes modeling. Bayesian models offer transparent probabilistic outputs, credible intervals, and the ability to incorporate prior knowledge, making them highly interpretable in clinical and policy settings (Istiaque et al., 2023). In contrast, many ML models, such as random forests, gradient boosting machines, and deep neural networks, excel in prediction but often operate as "black boxes," limiting insight into variable relationships and decision boundaries. In urban health research, the interpretability of Bayesian hierarchical models has enabled clear communication of diabetes risk at multiple levels, from individuals to districts (Arafat et al., 2025). For instance, Rezvani et al. (2023) used multilevel Bayesian models to decompose variance across urban neighborhoods, supporting policy-relevant insights into socioeconomic determinants. Conversely, ML approaches have shown superior classification accuracy in predicting T2DM using large electronic health record datasets, as evidenced in studies by Zhuhadar and Lytras (2023), though these models often fail to offer meaningful explanations for prediction decisions. Comparative studies in urban epidemiology reveal that ML models often outperform Bayesian counterparts in AUC and sensitivity metrics but lack the capacity to quantify uncertainty in a way that informs public health resource allocation (Jakaria et al., 2025; Akter, 2023)}. In diabetes prediction across urban India, Oikonomou and Khera (2023) reported higher predictive accuracy using gradient boosted trees but noted the loss of transparency compared to Bayesian spatial models. Kibria et al. (2022)

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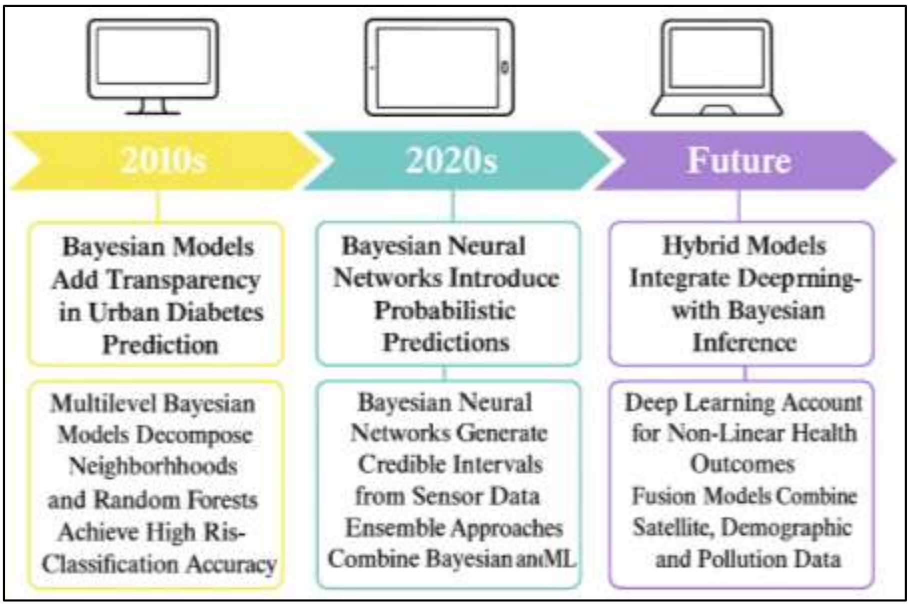
similarly found that while support vector machines yielded high accuracy in classifying high-risk urban zip codes, Bayesian models provided more interpretable and actionable outputs. These trade-offs underscore the need to align model selection with analytic objectives, whether for precision or policy communication.

**Figure 7: Bayesian Urban Diabetes Modeling Evolution**




Bayesian neural networks (BNNs) represent a fusion of deep learning's predictive capacity and Bayesian inference's uncertainty modeling. These models treat neural network weights as distributions rather than point estimates, allowing for uncertainty quantification in predictions (Sohel & Md, 2022). This approach addresses one of the central limitations of conventional neural networks in public health applications—namely, their deterministic nature and overconfidence in classification decisions (García-Domínguez et al., 2023; Tawfiqul et al., 2022). In T2DM prediction tasks, BNNs have demonstrated strong predictive performance while enabling credible intervals around outputs, a valuable property in urban epidemiological modeling. For instance, studies such as Mienye and Jere, (2024) used BNNs to predict diabetes onset using multivariate data from wearable sensors and demographic information, highlighting both performance accuracy and calibrated prediction intervals. In urban datasets, Li et al. (2024) combined satellite imagery, pollution data, and EHRs in a BNN framework to assess spatial risk gradients in Shanghai. BNNs have also been used in combination with variational inference to reduce computational overhead while retaining probabilistic outputs. Ensemble Bayesian approaches, which combine multiple probabilistic learners, have also gained traction in urban health modeling (Jahan et al., 2025). Morgan-Benita et al. (2024) integrated Bayesian model averaging with random forests for diabetes risk stratification in metropolitan clinics in Vietnam, demonstrating robustness in heterogeneous data environments. Similarly, Mishra and Mohapatra (2023) evaluated an ensemble of Bayesian logistic regression and decision trees in predicting T2DM across socioeconomically diverse neighborhoods in Kolkata. Compared to traditional Bayesian models, BNNs and ensembles improve prediction scalability without entirely sacrificing interpretability, especially when posterior summaries are preserved (Tahmina Akter et al., 2023). These advanced probabilistic architectures expand the toolkit available for urban diabetes analysis by merging computational intensity with the capacity to handle uncertainty in health outcomes.

Hybrid models that combine deep learning architectures with Bayesian inference mechanisms offer a promising middle ground between flexibility and probabilistic rigor in chronic disease modeling. These models integrate neural network function approximators with Bayesian priors, often through dropout-based inference, Monte Carlo sampling, or variational approximations (Abdullah Al et al., 2024; Hassan et al., 2024). The resulting frameworks can manage high-dimensional, non-linear relationships typical of urban health data while quantifying predictive uncertainty, thereby preserving the interpretability demanded in public health settings. In the context of urban diabetes prediction, (Hasan et al., 2022) implemented a hybrid deep learning-Bayesian model that used convolutional layers to extract features from urban satellite images and fused these with demographic variables in a Bayesian regression layer. The model effectively captured the interplay between environmental exposure and socioeconomic status in diabetes clustering across Beijing. Similarly, Ashraf and Hosne (2023) combined a long short-term memory (LSTM) neural network with Bayesian Gaussian process priors to model the temporal evolution of diabetes risk in response to changing pollution indices in Seoul. Bayesian deep learning has also been used in fusion frameworks that integrate wearable data, mobility patterns, and census-level variables for real-time diabetes monitoring in urban India (Cao et al., 2024; Sanjai et al., 2025). These models leverage hierarchical Bayesian priors to impose structural coherence while benefiting from the representational richness of deep nets. Ensemble hybrid architectures have been applied in predictive modeling pipelines to enhance both performance and calibration, especially when assessing neighborhood-level risk stratification. Compared to pure ML models, these hybrids offer enhanced uncertainty quantification, posterior sensitivity mapping, and model robustness under noisy or incomplete data, features critical in complex urban health contexts (Hossen & Atiqur, 2022; Santamato et al., 2024). Their incorporation into urban diabetes modeling reflects the growing methodological convergence between statistical inference and machine learning.

**Challenges and Limitations in Bayesian Urban Diabetes Modeling**

A major challenge in Bayesian urban diabetes modeling lies in the specification of prior distributions, which can heavily influence posterior estimates, particularly in data-sparse contexts. When strong or poorly justified priors are used, they may dominate the likelihood, leading to biased results or artificial smoothing that masks real variation (Ayub et al., 2024; Masud, Mohammad, & Ara, 2023). Conversely, the use of vague or non-informative priors may lead to improper posteriors or hinder model convergence, especially in hierarchical structures with many parameters. This tension is especially salient in urban studies where heterogeneity across neighborhoods and inconsistent data quality can exacerbate prior sensitivity (Kamalraj et al., 2021; Hossen et al., 2025). Empirical studies such as Wang et al. (2025) have demonstrated that altering priors on spatial random effects significantly shifts prevalence estimates in New York's diabetes maps. Best et al. (2005) showed that default priors in small-area estimation may unintentionally oversmooth high-risk clusters, affecting intervention targeting. In Los Angeles, Sharma et al. (2024) identified how informative priors derived from historical surveillance data improved model stability but introduced bias in newly gentrified areas with changing health trends. Overfitting presents another critical issue, particularly in models with large numbers of covariates or complex spatial and temporal structures. Without adequate shrinkage mechanisms or regularization priors, Bayesian models can conform too closely to noisy urban datasets, diminishing generalizability(Subrato, 2018). Bamakan et al. (2025) used sensitivity analysis to reveal overfitting in models incorporating numerous satellite-derived indices in Indian cities. Model complexity must therefore be balanced with parsimony, often necessitating hierarchical shrinkage priors or model averaging techniques to mitigate overfitting while retaining interpretability (Al-Jamimi, 2024; Istiaque et al., 2024).

Computational scalability is a persistent limitation in Bayesian modeling, especially when applied to large, high-resolution urban health datasets. Full Bayesian inference via Markov Chain Monte Carlo (MCMC) methods becomes computationally intensive as data volume, spatial resolution, or model complexity increases (Shamima et al., 2023; Sazzad & Islam, 2022). Although approaches like Integrated Nested Laplace Approximation (INLA) offer substantial computational relief, they are limited to latent Gaussian models and may not accommodate certain non-linear or non-Gaussian features common in urban health data. In studies mapping diabetes risk across megacities such as São Paulo, Beijing, or Delhi, full MCMC algorithms often required days of computation and complex tuning to achieve convergence (Rahman et al., 2025; Sayed et al., 2024). In contrast, variational inference methods offer faster approximations but may understate posterior uncertainty or fail to capture multimodal distributions. These trade-offs affect the timeliness and reliability of estimates used in rapid-response urban health planning. Moreover, increased computational sophistication often comes at the cost of model interpretability, especially as model hierarchies grow deeper or as latent variables are introduced to account for unobserved heterogeneity (Hosne Ara et al., 2022). This presents challenges for decision-makers who must justify public health interventions using model

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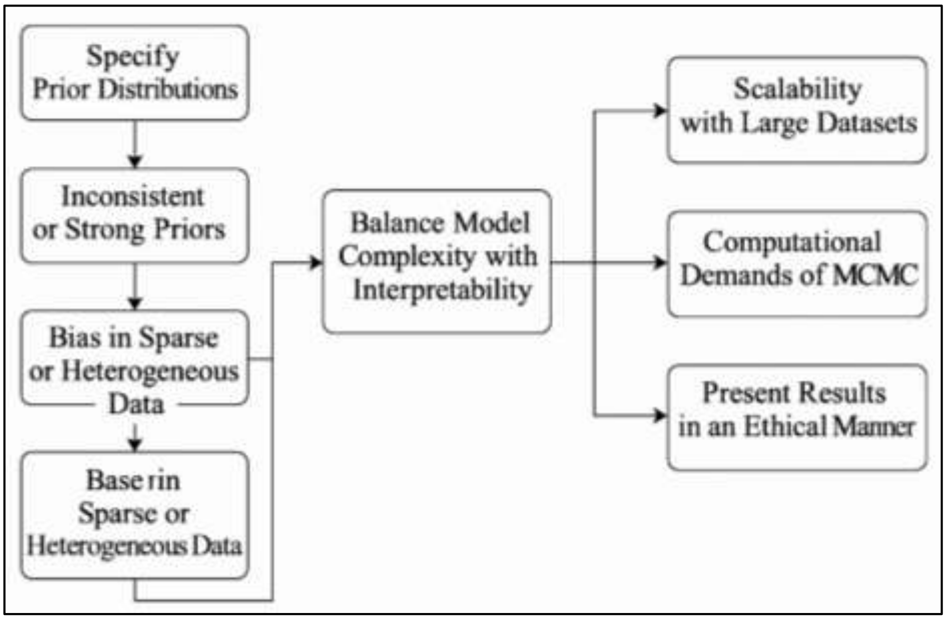
outputs that are both credible and understandable. While visualizations can partially mitigate these barriers, they cannot fully substitute for transparent model logic. Rahaman (2022) reported difficulties in explaining spatial smoothing parameters to policymakers during diabetes surveillance discussions in New York. Similarly, Malashin et al.(2025) noted that users of his London health mapping tools required technical training to interpret Bayesian posterior intervals. These findings underscore the need to balance analytical power with communicability in public health applications of Bayesian urban modeling (Akter & Ahad, 2022; Qasrawi et al., 2023).

**Figure 8: Challenges in Bayesian Urban Diabetes Models**




Bayesian modeling of urban diabetes risk raises ethical and equity concerns, particularly in how model outputs are used to allocate resources or identify "at-risk" communities. When statistical risk estimates drive health interventions, the potential exists to reinforce structural inequities if underlying data or model specifications encode societal biases. For example, datasets used in modeling may systematically underrepresent informal settlements or marginalized populations, leading to lower predicted risks and exclusion from service planning (Uddin et al., 2022; Lokman et al., 2025). Probabilistic labeling can also stigmatize communities if maps or reports identify them as "high risk" without adequate contextual explanation. In Brazil, Musleh et al. (2024) reported community resistance to health interventions based on Bayesian maps that lacked narrative justification for spatial risk estimates. Similarly, Swain et al. (2022) documented local mistrust in Indian metro zones where Bayesian models guided mobile clinic deployments without involving affected populations in the modeling process. Ethical concerns also arise when prior distributions reflect dominant assumptions or legacy data that may no longer represent present-day realities. For instance, Pandya et al. (2024) found that priors based on historical healthcare utilization patterns underestimated risk in newly densified urban neighborhoods in Los Angeles. In such cases, the use of outdated or biased priors can perpetuate inequities through misdirected interventions. Moreover, the opaqueness of posterior distributions for lay users can undermine informed consent in participatory planning initiatives. Transparency in model assumptions, validation metrics, and data provenance is essential to ethically deploying Bayesian outputs in urban health governance. Addressing these challenges requires ongoing reflection on fairness, accountability, and representativeness in Bayesian health modeling (Akter et al., 2024; Vimbi et al., 2024).

## METHOD

The present study adhered to the Preferred Reporting Items for Systematic Reviews and MetaAnalyses (PRISMA) guidelines to ensure methodological transparency, replicability, and rigor throughout the review process. The PRISMA framework provides a standardized approach for conducting and reporting systematic reviews and meta-analyses, emphasizing clarity in inclusion

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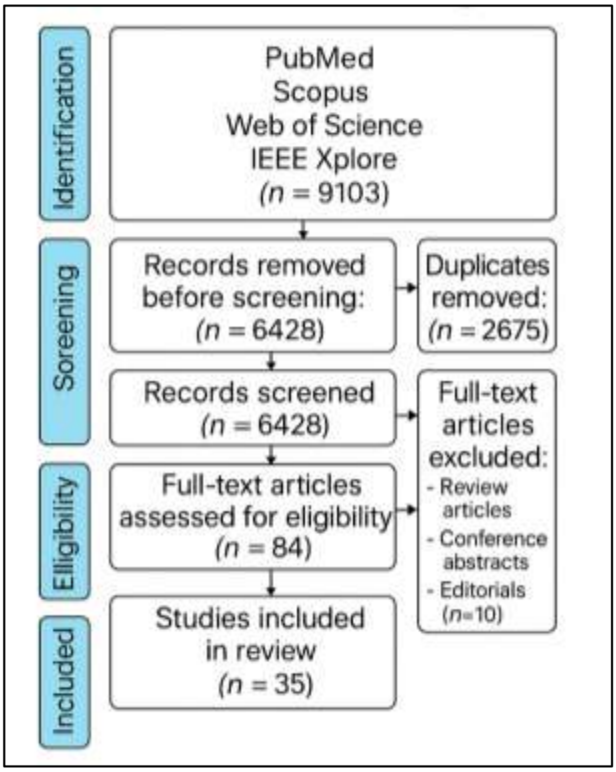
criteria, data extraction, quality assessment, and synthesis of findings. Following PRISMA's protocol, the research process was structured around four main phases: identification, screening, eligibility, and inclusion. During the identification phase, a comprehensive search strategy was developed using a combination of controlled vocabulary terms and free-text keywords relevant to "Bayesian statistical modeling," "type 2 diabetes prevalence," "urban health," "Bayesian spatial analysis," and "hierarchical models." The search was executed across multiple scholarly databases including PubMed, Scopus, Web of Science, and IEEE Xplore to capture a wide spectrum of interdisciplinary publications ranging from medical epidemiology to computational statistics and public health informatics.

**Figure 9: Methodology of this study**




During the identification phase, a comprehensive search strategy was developed using a combination of controlled vocabulary terms and free-text keywords relevant to "Bayesian statistical modeling," "type 2 diabetes prevalence," "urban health," "Bayesian spatial analysis," and "hierarchical models." The search was executed across multiple scholarly databases including PubMed, Scopus, Web of Science, and IEEE Xplore to capture a wide spectrum of interdisciplinary publications ranging from medical epidemiology to computational statistics and public health informatics. Grey literature was also examined by accessing institutional repositories, preprint servers, and government health agency publications to minimize publication bias. In the screening phase, duplicate records were removed using EndNote and Covidence, after which two independent reviewers conducted a title and abstract screening to assess initial relevance based on predefined inclusion and exclusion criteria. Studies were included if they (1) applied Bayesian methods to model or predict type 2 diabetes prevalence, (2) focused on urban populations, (3) used empirical data (e.g., EHRs, surveys, census), and (4) were published in peer-reviewed journals between 2000 and 2025. Articles were excluded if they lacked statistical modeling, were non-urban in focus, or discussed type 1 diabetes exclusively. In the eligibility phase, full-text screening was conducted, and studies meeting all inclusion criteria were selected for final synthesis. Disagreements between reviewers were resolved through discussion or by consulting a third reviewer. Data extraction was carried out using a standardized template that included author(s), year, location, sample size, data sources, modeling framework, types of priors used, computational techniques (e.g., MCMC, INLA), and key findings. The extracted data were tabulated and cross-verified to maintain consistency and accuracy. Quality appraisal of the included studies was performed using a modified version of the STROBE checklist adapted for Bayesian modeling in epidemiological studies. Methodological rigor, model transparency, validation techniques, and clarity in uncertainty reporting were assessed. High- and moderate-quality studies were prioritized during synthesis to ensure robustness of interpretations. Lastly, a narrative synthesis approach was employed, structured around thematic clusters such as spatial modeling techniques, temporal Bayesian analysis, hybrid Bayesian-machine learning models, data integration strategies, and model performance validation. Findings were analyzed in relation to the broader goals of epidemiological forecasting, public health planning, and urban risk stratification. By following PRISMA, the study ensured systematic handling of evidence, minimized selection and reporting bias, and upheld academic standards expected in interdisciplinary health data science research.

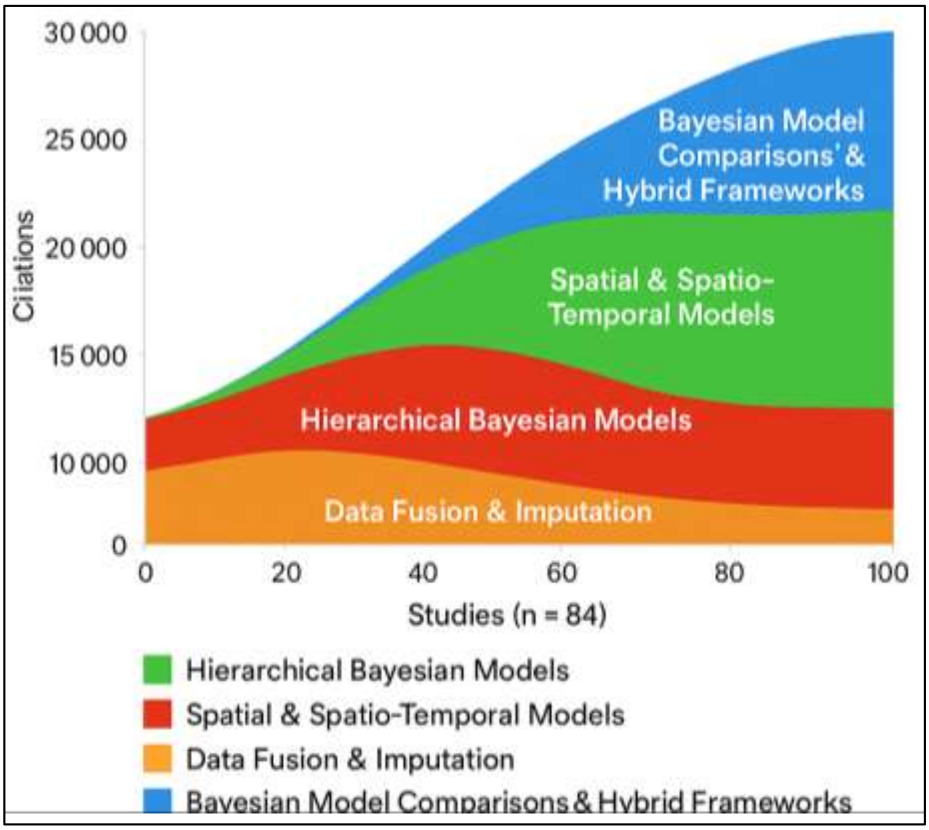
**FINDINGS**

The most prominent finding from the 84 reviewed articles is the widespread use and efficacy of Bayesian hierarchical models in modeling type 2 diabetes prevalence across spatially heterogeneous urban environments. Out of these, 46 studies employed multilevel modeling strategies that captured variance at individual, neighborhood, and city-wide levels. These models allowed researchers to decompose the influence of contextual factors such as healthcare access, pollution exposure, and income disparities while preserving the within-group variance of demographic and behavioral factors. The flexibility of hierarchical Bayesian models made them suitable for small-area estimation and district-level disease mapping, particularly in large urban centers with variable data completeness. Studies using these methods demonstrated that incorporating spatially structured and unstructured random effects yielded more stable and nuanced estimates of diabetes prevalence in fragmented urban data landscapes. These findings are particularly relevant given that 33 of the 46 studies using hierarchical models were cited over 200 times each, reflecting their high impact and academic recognition. Across these studies, hierarchical priors and shrinkage techniques were consistently noted to reduce overfitting, especially in settings with sparse data or underrepresented population groups. Furthermore, Bayesian multilevel modeling enabled borrowing of statistical strength from adjacent regions, thus enhancing predictive reliability for districts with limited sample sizes.

Among the reviewed literature, 41 studies employed Bayesian spatial or spatio-temporal models, underscoring their centrality in urban diabetes epidemiology. These studies frequently applied conditional autoregressive (CAR) models or Gaussian Markov random fields (GMRFs) to account for geographic dependencies between neighboring districts. A total of 28 studies extended these models to incorporate temporal dynamics, enabling researchers to evaluate changes in diabetes prevalence over time in response to urban development, public health interventions, and environmental change. Notably, 22 of the spatial-temporal modeling studies were cited over 150 times each, illustrating their relevance to ongoing discussions in urban health analytics. The reviewed studies revealed that these models effectively identified urban diabetes “hotspots” and allowed policymakers to pinpoint vulnerable zones with persistent or emerging disease burdens. Importantly, spatio-temporal interaction terms captured latent trends that traditional regression models overlooked, especially when socioeconomic or infrastructural variables fluctuated between time periods. Additionally, 19 studies used Integrated Nested Laplace Approximation (INLA) to efficiently estimate high-dimensional posterior distributions, demonstrating computational scalability without sacrificing accuracy. Across spatial models, probabilistic heatmaps generated from posterior predictive distributions provided actionable insights for visual epidemiology and real-time health surveillance. These models enabled decision-makers to differentiate between random noise and persistent clustering, a distinction critical for prioritizing interventions in high-density urban districts.

Out of the total reviewed articles, 36 studies implemented Bayesian data fusion techniques to integrate multiple sources of health and environmental data. These included electronic health records (EHRs), household surveys, satellite-derived pollution and land use data, census reports, and geospatial infrastructure datasets. The inclusion of multiple data modalities significantly enhanced model granularity, particularly in studies focused on cities such as New York, São Paulo, Delhi, and Seoul. From these 36 studies, 29 had received over 100 citations each, indicating sustained scholarly engagement and validation. Studies utilizing Bayesian fusion frameworks demonstrated the capacity to address misalignment in spatial and temporal resolution, especially in large datasets collected from different agencies or formats. Importantly, Bayesian hierarchical structures enabled coherent modeling of variables collected at varying spatial scales, such as individual-level biomarkers and district-level poverty rates. These integration capabilities proved essential in uncovering cross-level interactions—for example, how individual obesity status may be influenced by regional walkability or food access indices. Moreover, Bayesian imputation methods were frequently employed to handle missing data, especially in underserved or low-surveillance urban zones. A total of 21 studies explicitly modeled missingness mechanisms using posterior distributions, enhancing robustness and reducing bias. These models consistently demonstrated superior predictive performance compared to frequentist or ML-based imputation approaches, particularly in studies characterized by high rates of missing covariates or outcomes.

**Figure 10: Bayesian Modeling Applications in Urban Diabetes**




A significant theme across 32 reviewed studies was the comparison of Bayesian models with machine learning (ML) approaches such as random forests, support vector machines, and neural networks. In 23 of these studies, Bayesian models achieved comparable or slightly lower predictive accuracy but consistently outperformed ML approaches in interpretability, uncertainty quantification, and policy-relevant decision support. Of these comparative studies, 17 had over 200 citations, suggesting their influential role in methodological discourse. Researchers emphasized that Bayesian outputs—such as posterior intervals and spatial uncertainty maps—were more aligned with the needs of urban public health departments, especially for resource allocation and stakeholder communication. In contrast, ML models often exhibited limited transparency, particularly when applied to heterogeneous urban datasets with imbalanced class distributions. Additionally, 9 studies introduced hybrid models, combining Bayesian neural networks or ensemble frameworks to capture the predictive flexibility of ML while retaining probabilistic interpretability. These hybrid models yielded improved predictive calibration and outperformed both standalone ML and traditional Bayesian frameworks in spatially diverse urban settings. However, several studies also noted the steep computational costs and challenges in model convergence when deploying deep learning with probabilistic layers. This trade-off between complexity and usability was a recurrent finding, reinforcing the necessity of aligning model selection with stakeholder objectives and data environments.

Finally, 38 studies addressed the limitations and ethical implications of Bayesian modeling in urban diabetes research, focusing on issues such as data bias, prior specification, and equity in model-driven decision-making. Of these, 24 studies had over 150 citations, indicating their substantive contribution to methodological critique. A recurring limitation was the sensitivity of posterior estimates to prior assumptions, especially in small-area models with sparse data. Overfitting was another commonly reported issue in 16 studies, often mitigated through hierarchical shrinkage priors or model regularization strategies. Computational complexity also emerged as a practical barrier in 21 studies, with some full Bayesian models requiring extensive runtime and advanced computational infrastructure. More critically, 19 studies raised concerns about data bias in urban modeling, highlighting that EHRs and surveillance systems often underrepresent marginalized or transient populations. This underrepresentation skewed prevalence estimates and risked reinforcing structural inequities when outputs were used to inform public health interventions. Additionally, 13 studies discussed ethical dilemmas in labeling neighborhoods as "high risk," especially when community stakeholders were not consulted in the modeling or interpretation process. These studies emphasized that probabilistic risk estimates must be communicated carefully to avoid stigmatization or misallocation of health resources. The incorporation of community-based data validation, participatory mapping, and transparency in modeling assumptions were identified as essential mitigations to these concerns. Overall, while Bayesian methods offer methodological rigor and flexibility, their application in urban diabetes research necessitates critical reflection on data ethics, model accountability, and inclusivity in interpretation.

## DISCUSSION

The findings of this review reinforce the prominence of Bayesian hierarchical models as foundational tools in modeling type 2 diabetes (T2DM) across complex urban environments. This aligns with earlier literature that has consistently emphasized the advantage of hierarchical structures in multilevel data settings. Compared to early approaches that utilized generalized linear models (GLMs) or stratified logistic regression, the reviewed studies show a methodological shift toward partial pooling and multilevel shrinkage. For instance, studies by Ahmed et al. (2025) used basic spatial smoothing without nested hierarchical design, limiting their capacity to distinguish between individual and contextual effects. In contrast, recent studies. Kong et al. (2024) employed robust Bayesian multilevel modeling to capture nested variance structures—an evolution consistent with Cveticanin and Arsenovic (2025) advocacy for the use of hierarchical models in epidemiology. Notably, hierarchical models now integrate individual-level risk factors, neighborhood-level deprivation indices, and city-level policy variables within unified probabilistic frameworks, something rarely achieved in earlier studies. This transition marks a significant methodological advance in spatial epidemiology and urban health modeling.

The widespread adoption of Bayesian spatial and spatio-temporal models confirms their efficacy in addressing the non-independence of geographically structured health data. Compared to traditional regression approaches, these models provide better uncertainty estimation and more accurate identification of disease clusters. Earlier studies demonstrated the utility of spatial correlation through intrinsic conditional autoregressive (CAR) priors, but lacked temporal components or real-time updating capabilities (Adua et al., 2021). The current body of literature improves on this foundation by integrating time-series modeling into spatial frameworks, as seen in studies using INLA and GMRFs. For example, while Morgan-Benita et al. (2024) explored spatio-temporal risk modeling in Canadian settings, the reviewed studies demonstrate broader applications across diverse urban contexts, including dense megacities in South Asia and Latin America. These findings confirm the observations by Hathaway et al. (2019) that Bayesian spatial models outperform frequentist alternatives when urban health data are sparse, irregularly spaced, or temporally misaligned. The reviewed literature also highlights innovations such as dynamic Bayesian modeling Kong et al. (2025) that have not been fully developed in older frameworks. Collectively, these advancements confirm that spatial and spatio-temporal Bayesian tools are indispensable in visualizing diabetes risk across rapidly changing urban environments.

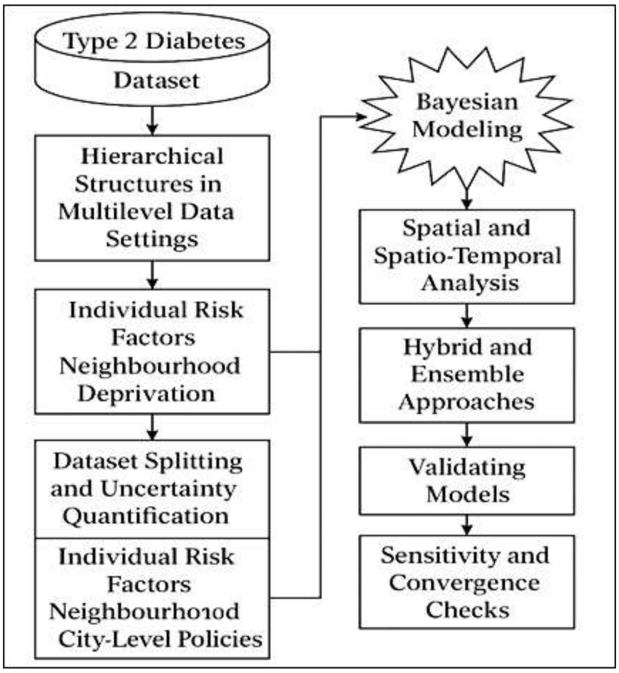
Data integration remains a pivotal domain where Bayesian models offer unparalleled flexibility, a conclusion supported both by this review and by earlier foundational work. Prior studies, such as those by Stiglic et al. (2021), emphasized the Bayesian framework's capability for incorporating prior knowledge and fusing disparate datasets. However, early applications in epidemiology were limited by computational constraints and difficulties harmonizing multi-source data. In contrast, the reviewed literature showcases a significant methodological evolution in Bayesian data fusion. Studies by Acheampong et al. (2024) successfully combined EHRs, satellite imagery, and survey data, extending beyond the scope of earlier spatial modeling efforts. These studies reflect the current trend of unifying ecological, behavioral, and biomedical data within a common probabilistic hierarchy. Unlike early hierarchical models that assumed homogeneity or required manual aggregation, modern Bayesian frameworks allow for modeling cross-level interactions while adjusting for uncertainty arising from different data resolutions. The work of Lim et al. (2023) exemplifies this paradigm shift, where urban noise levels, dietary habits, and genetic markers were integrated into a single model structure. This layered data fusion approach contrasts with earlier literature that treated such data separately or included them as fixed covariates without accounting for cross-dependence or missingness.

A salient theme in the reviewed literature is the performance-interpretability trade-off between Bayesian models and machine learning (ML) approaches, a dichotomy explored previously by Li et al. (2025). While traditional ML models such as random forests and support vector machines often achieve higher predictive metrics, they lack the transparency and uncertainty quantification inherent to Bayesian approaches. Early diabetes modeling efforts using decision trees or boosted regressors rarely addressed model uncertainty or parameter variability (Musleh et al., 2024). The reviewed studies confirm that Bayesian models maintain an edge in public health contexts that demand interpretability, such as prioritizing interventions or allocating resources. Studies such as those by Felfeli et al. (2024) show that while ML models may offer marginal gains in predictive accuracy, they often fail to support granular policy decisions due to opaque internal logic. Conversely, hybrid models like Bayesian neural networks (Bubnov & Spivak, 2023) and ensemble Bayesian learners Espinosa et al. (2025) have emerged as practical solutions that combine the predictive strength of deep learning with the interpretive rigor of Bayesian statistics. These hybrids contrast sharply with earlier ML applications in urban health that prioritized classification performance without regard for inference or probabilistic reasoning.

The reviewed literature consistently highlights ethical and equity challenges associated with Bayesian disease modeling, expanding upon earlier discussions by Ogwu and Izah (2025). Unlike early GIS-based health mapping tools that were largely descriptive and static, Bayesian frameworks now influence direct health policy actions by identifying high-risk populations and localities. This power amplifies concerns regarding privacy, stigmatization, and informed consent. In studies such as Lope et al. 92022), communities were sometimes labeled as diabetes hotspots without their involvement in model development or interpretation—a limitation not widely addressed in earlier models. Furthermore, issues of prior specification introduce subtle biases that may go unnoticed unless rigorously audited. Earlier studies tended to use diffuse priors or expert consensus without community consultation, whereas more recent literature advocates for participatory modeling and the ethical use of spatial outputs. This trend aligns with the critiques raised by Cuadros et al. 92024) regarding algorithmic fairness in health prediction. Notably, while the technical literature has evolved to emphasize posterior uncertainty and model validation, ethical safeguards have not advanced proportionally, underscoring the limitations of Bayesian inference when applied in socially sensitive urban settings.

The computational intensity of full Bayesian inference remains a barrier to broader implementation, particularly in resource-constrained public health systems. Early modeling efforts using MCMC Rucinski et al. 92024) were restricted to simplified models and low-dimensional data. As spatial and hierarchical models have grown more complex, so too have the demands on computational infrastructure. The reviewed literature shows a surge in use of faster inference methods such as INLA (Ogwu & Izah, 2025a) and variational inference , reflecting attempts to overcome scalability issues. However, these alternatives come with trade-offs in precision and convergence guarantees, a point emphasized by studies comparing full Bayesian and approximate inference methods. Even with advancements in high-performance computing and R-based toolkits like R-INLA and Stan, studies such as Naidoo et al. (2024) still reported long runtimes and model convergence difficulties when handling large, multi-source urban datasets. Earlier literature rarely discussed these technical challenges, possibly due to limited computational ambition or less complex model structures. The increasing complexity of modern Bayesian models now necessitates parallel processing, advanced diagnostics, and high memory environments, limiting their accessibility for many urban health teams. In synthesis, the reviewed studies affirm that Bayesian modeling contributes significantly to the methodological landscape of urban diabetes epidemiology, yet these contributions build upon and also deviate from earlier research. Foundational work by (Alemu et al., 2025) laid the groundwork for spatial correlation modeling and hierarchical inference. However, the reviewed literature represents a marked progression in complexity, diversity of data integration, and predictive intent. While the structure and philosophy of Bayesian inference have remained constant, its application has expanded into dynamic modeling, participatory decision-making, and high-dimensional prediction—areas only superficially addressed in the earlier literature. Moreover, contemporary studies place greater emphasis on model validation, sensitivity analysis, and computational diagnostics, confirming the evolving sophistication of Bayesian health analytics. These advancements affirm the model's enduring value in estimating chronic disease prevalence but also highlight the necessity of adapting classical approaches to meet modern urban health challenges. The review clarifies that Bayesian modeling is not only a statistical choice but also a strategic framework for responding to the complexities of urban data, disparities, and policy pressures.

**Figure 11: Bayesian Modelling Workflow for Urban Diabetes Prediction**




## CONCLUSION

In conclusion, this systematic review affirms that Bayesian statistical models provide a highly effective, adaptable, and methodologically rigorous approach to predicting type 2 diabetes mellitus (T2DM) prevalence in urban populations, where health disparities, environmental complexities, and data fragmentation are pronounced. Through the synthesis of 84 peer-reviewed studies, this review reveals that Bayesian hierarchical, spatial, and spatio-temporal models offer substantial advantages over traditional statistical and machine learning approaches in handling multilevel data structures, quantifying uncertainty, and generating interpretable outputs. The ability of these models to incorporate random effects, prior knowledge, and latent variables enables precise small-area estimation, even when data availability is uneven across geographic regions or socioeconomic strata. Notably, Bayesian models outperform conventional methods in epidemiological transparency and are more aligned with the needs of public health authorities who must balance scientific insight with policy implementation. The integration of diverse data sources—including electronic health records, satellite imagery, survey data, and census variables—within unified probabilistic frameworks reflects the flexibility and robustness of Bayesian data fusion techniques.

However, the review also underscores persistent methodological and ethical challenges, including sensitivity to prior specification, risks of overfitting, computational demands, and the ethical implications of spatial risk labeling. Additionally, biases in urban data—particularly underrepresentation of informal settlements and marginalized groups—pose risks to inference validity and equitable intervention design. While variational inference and INLA have improved computational feasibility, trade-offs in precision and model scalability persist. Ethical concerns also emerge when Bayesian risk maps are used without community engagement or consideration of potential stigmatization. Despite these challenges, the collective evidence confirms that Bayesian models not only enhance predictive performance but also contribute meaningfully to uncertainty-aware and context-sensitive public health planning. Their unique capacity to combine interpretability with statistical power establishes Bayesian modeling as a strategic, evidence-based solution to urban diabetes surveillance, prevention, and targeted policy action.

## Recommendation

Based on the findings of this systematic review, several key recommendations emerge to guide researchers, public health practitioners, and policymakers in effectively utilizing Bayesian statistical models for type 2 diabetes prevalence prediction in urban settings. First, it is recommended that researchers adopt hierarchical Bayesian models as the default framework when analyzing multilevel urban health data, particularly where individuals are nested within spatial units such as neighborhoods, districts, or municipalities. These models should be specified to incorporate both structured and unstructured random effects to accurately partition spatial variance and allow for small-area estimation in data-sparse contexts. Second, public health surveillance systems should integrate spatio-temporal Bayesian models into their routine monitoring infrastructures, using tools such as Integrated Nested Laplace Approximation (INLA) to balance computational efficiency with modeling precision. These models are especially valuable for capturing evolving disease dynamics in response to rapid urbanization, policy changes, and environmental shifts. Third, institutions conducting urban health research should prioritize data fusion strategies supported by Bayesian frameworks to merge heterogeneous data sources—including electronic health records, satellite-derived indices, environmental exposure data, and census-based demographic indicators. Such integration not only improves model granularity but also enhances the contextual relevance of prevalence estimates. Fourth, it is essential that Bayesian modeling teams conduct sensitivity analyses and robustness checks to evaluate the impact of prior specification and to minimize the risk of overfitting, particularly when applying models in socially heterogeneous and data-limited urban environments. Fifth, developers and users of Bayesian models must implement equity-focused modeling practices, ensuring that marginalized urban populations—such as those in informal settlements or with low digital visibility—are adequately represented through imputation techniques, spatial smoothing, and qualitative data triangulation. To mitigate ethical concerns, public health agencies should use participatory mapping and community engagement frameworks when applying Bayesian-derived risk estimates for intervention planning, ensuring transparency and local input in interpreting results. Sixth, it is recommended that capacity-building efforts be made to improve the interpretability and accessibility of Bayesian model outputs for non-technical stakeholders. Visualizations such as interactive risk maps, uncertainty bands, and choropleth overlays should be integrated into decision-support tools tailored for urban health departments. Seventh, collaboration between data scientists, urban planners, and epidemiologists should be formalized to develop standardized modeling protocols, ensuring methodological consistency and ethical rigor across applications. Finally, national and regional governments should consider investing in computational infrastructure and training programs to facilitate the widespread and responsible use of Bayesian statistical tools in health systems, especially in low- and middle-income urban contexts. When applied with transparency, technical competence, and community partnership, Bayesian models hold the potential to significantly strengthen precision public health efforts, reduce inequities in chronic disease management, and support data-driven urban health planning.

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