



# Hybrid AI and Big Data Frameworks for Smart City Infrastructure Planning

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**ABSTRACT:** Smart cities constitute poles for the economic, cultural, and social interactions that shape the evolution of areas. The resilience of cities is key to facing environmental, technological, or health crises. Resilience is related to the capacity for quickly taking optimal decisions in response to crises, and hence to the ability to timely absorb and analyse large volumes of data. Data are generated continuously by urban systems and reside in different databases held by different stakeholders. Hybrid AI and Big Data frameworks enable real-time responses to crises, implement data-driven and simulative models, and produce data-science, model-driven and Mixed-AI Intelligent Agents for the modelling of urban crises. However, applying such frameworks in planning urban systems are highly demanding.

The urban systems and services enabling the operations of cities and urban networks are complex, multidisciplinary, and partitioned within traditional areas of expertise, both in engineering and in information technologies. External funding is mostly project based, and concentrated on individual sectors, and not on an integrated planning approach. Most importantly, real-time responses to crises require data-driven models able to reproduce an emergency. For the integrated planning of transport, energy, and communication systems, real-time traffic prediction, demand signalling, and infrastructure adaptation are mandatory. For intersections of two roads, real-time data analytics require prediction of the expected intensity of flows.

**KEYWORDS:** Smart City Resilience, Hybrid AI and Big Data Frameworks, Urban Crisis Modeling, Real-Time Urban Data Analytics, Data-Driven Urban Planning, Mixed-AI Intelligent Agents, Urban Systems Integration, Real-Time Traffic Prediction, Infrastructure Adaptation Strategies, Urban Energy and Transport Coordination, Crisis Response Optimization, Multidisciplinary Urban Systems Engineering, Predictive Flow Modeling at Intersections, Data-Science-Driven Urban Governance, Simulation-Based Emergency Management.

## I. INTRODUCTION

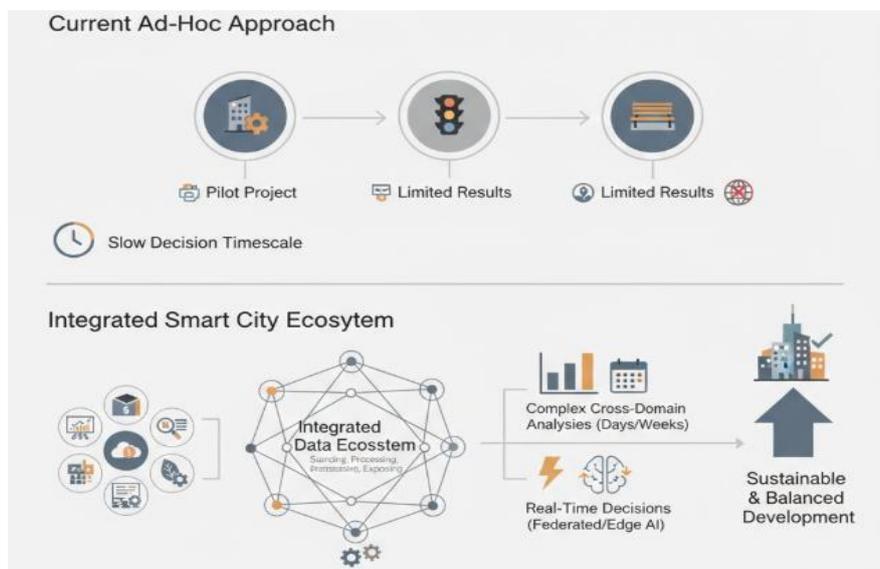
Urban challenges including climate change, social equity, and resource scarcity have increased interest in innovative approaches for building and managing cities. Smart city frameworks aim to make urban infrastructure more responsive to both anticipated and emergent events. Such cities generate vast amounts of data, enabling stakeholders to satisfy a wide variety of requests for real-time, historical, and predictive information. Data science, artificial intelligence (AI), machine learning, and other techniques are employed to extract knowledge from these datasets. In the context of urban infrastructure, AI combined with big data can support decision making across many different domains, including transportation, energy, building and water management, and disaster management. However, the interplay among such diverse applications is rarely investigated in a cohesive and systematic manner, especially in the context of infrastructure planning.

This work investigates the role of big data and hybrid AI in urban infrastructure planning. Community resilience to stressors such as disasters, pandemics, or climate change strongly depends on the response of interconnected urban transport, energy, communication, and building infrastructure systems. Integrated data spanning these domains facilitate cross-domain applications and are important for understanding, modelling, and predicting their interactions. Recent advances in generative AI and LLMs create new opportunities for data generation, fusion, and multimodal integration. Federated and edge AI frameworks enable new AI applications in smart cities. These frameworks support the increasingly sensitive nature of city data and play an important role in privacy-preserving design. Hybrid modelling approaches that combine mechanistic models with data-driven models or models trained for domain transfer enable new scenario-analysis capabilities. Cloud-based big data platforms continue to provide the underlying data ingestion, integration, and processing capabilities, but recent work also pilots their use on-premises (rather than on a public cloud) for high-availability scenarios—supporting a closed-loop infrastructure for integrated data collection and decision support.

### 1.1. Overview and Significance of Smart Cities

Achieving sustainable and balanced social, economic, and environmental development is the main goal of smart cities. The associated investments have been steep and despite apparent progress, the majority of existing smart city projects have shown an ad-hoc, piecemeal approach that often lacks overall coherence. A prevalent model is that of a highly funded pilot project that covers a narrow functional domain, is integrated from the ground up, and implemented in one geographical area. Limited results from piloting, however, cannot be necessarily extrapolated across large parts of a city and do not contribute to achieving overall smart city objectives. The existing mismatch between decision-making timescales and type of analysis to support decisions represents one of the main hurdles for smart cities. Achieving true smartness requires a different approach that considers formative assessments and predictive scenario analysis across interconnected domains at the metropolitan scale.

Advancing technologies generate considerable amounts of data across multiple domains, thereby facilitating decision-making processes. However, data of many types and formats are generated from heterogeneous data sources with different frequency and scale, leading to data silos that block the development of cross-domain applications. An integrated data ecosystem is needed for sourcing, processing, and exposing integrated data products for enabling complex cross-domain analyses and visualizations. During data-driven decision making in the social, economic, and environmental domains, large volumes of data are typically used, cleaned, filtered, transformed beyond recognition, integrated into single datasets, generalized, and aggregated. Such pipelines may take days or weeks to complete. However, for real-time decision making, architectural paradigms such as federated or edge artificial intelligence (AI) can be deployed to generate quick short-term forecasts or recommendations that feed back into the system or are used to control physical, cybernetic, or virtual subsystems in a closed-loop manner. The truly smart city should support such cross-domain analyses and recommendations across interconnected domains at the metropolitan scale.



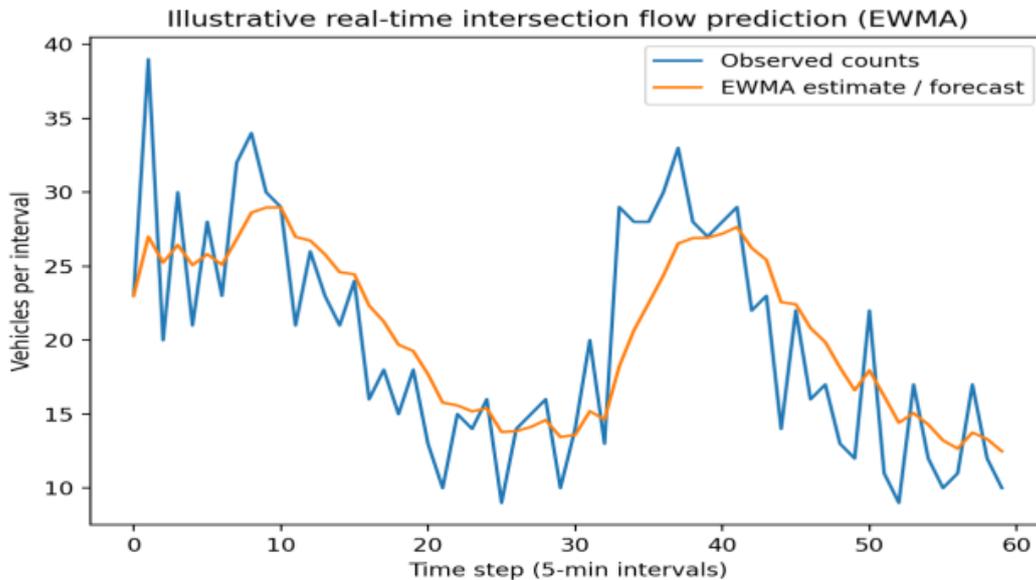
**Fig 1: Beyond Pilot Paradigms: An Integrated Data Ecosystem for Cross-Domain Decision Support and Real-Time Governance in Smart Cities**

## II. CONCEPTUAL FOUNDATIONS

The effective data integration required to enable hybrid AI and big data applications in smart city infrastructure planning relies on the concept of a data ecosystem. A data ecosystem comprises interconnected data sources whose contents can be consumed and shared by different stakeholders in a manner similar to biological ecosystems in which components are interconnected in order to sustain various living organisms. The availability of an integrated set of real-time or near-real-time data, combined with an appropriate decision-making algorithm, allows for the enhancement of several aspects of urban ecosystems and services. The concept of a data ecosystem is closely related to other foundational theories, concepts, and frameworks of smart city research and practice, including data provenance, data supply chain, formal semantics, data ontology, data governance frameworks, and ethical data governance frameworks. Four intertwined aspects allow the integration of data to create a data ecosystem: the processing and preparation of raw data from heterogeneous streams; their formal integration and encoding through provenance, supply-chain, and



ontological perspectives; the adoption of the Internet of Things and streaming technologies to facilitate real-time data access and variability analysis; and the collaboration among the smart city stakeholders involved in the movement of the data and the decisions that derive from their consumption. When the mechanisms for integrating the real-time data produced by various entities are in place, high-quality integrated data are available either for operators in charge of specific city services (for operational purposes) or for researchers, planners, private companies, and public authorities.



**Equation 1) Predictive flow modeling at intersections: “expected intensity of flows”**

**1.1 Model definition**

Let  $N(t)$  be the number of vehicles arriving to an approach (lane/group) up to time  $t$ . Assume arrivals follow a **non-homogeneous Poisson process** with intensity  $\lambda(t)$  (vehicles per unit time):

- Probability of  $k$  arrivals in a small interval  $[t, t + \Delta t)$ :

$$P(N(t + \Delta t) - N(t) = k) \approx \frac{(\lambda(t)\Delta t)^k}{k!} e^{-\lambda(t)\Delta t}$$

**1.2 Expected flow in a decision interval (step-by-step)**

Let the signal controller act over an interval  $[t, t + \tau]$ . Define:

$$X = N(t + \tau) - N(t)$$

For a non-homogeneous Poisson process:

$$X \sim \text{Poisson}(\Lambda(t, \tau))$$

where the integrated intensity is:

$$\Lambda(t, \tau) = \int_t^{t+\tau} \lambda(s) ds$$

**Therefore the expected arrivals (expected intensity over the interval) are:**

$$\mathbb{E}[X] = \Lambda(t, \tau) = \int_t^{t+\tau} \lambda(s) ds$$

Special case (locally constant rate over the interval): if  $\lambda(s) \approx \lambda$ ,

$$\mathbb{E}[X] = \lambda\tau$$

**1.3 Estimating  $\lambda$  from streaming counts (MLE derivation)**

Suppose you observe counts  $x_1, \dots, x_m$  in equal windows of duration  $\tau$ , and assume constant rate  $\lambda$  across those windows:

Then  $x_i \sim \text{Poisson}(\lambda\tau)$ .



**Likelihood**

$$L(\lambda) = \prod_{i=1}^m \frac{(\lambda\tau)^{x_i}}{x_i!} e^{-\lambda\tau}$$

**Log-likelihood**

$$\ell(\lambda) = \sum_{i=1}^m [x_i \ln(\lambda\tau) - \ln(x_i!) - \lambda\tau]$$

Differentiate and set to zero:

$$\frac{d\ell}{d\lambda} = \sum_{i=1}^m \left( \frac{x_i}{\lambda} - \tau \right) = \frac{1}{\lambda} \sum x_i - m\tau = 0$$

Solve for  $\lambda$ :

$$\hat{\lambda} = \frac{\sum_{i=1}^m x_i}{m\tau}$$

This  $\hat{\lambda}$  is the real-time estimate of “expected intensity of flows” the calls for .

**1.4 Simple real-time predictor (EWMA) for  $\lambda(t)$**

A common streaming estimator is **EWMA** on observed counts  $x_t$ :

$$\hat{x}_t = \alpha x_t + (1 - \alpha)\hat{x}_{t-1}, \quad 0 < \alpha \leq 1$$

If each step corresponds to a window  $\tau$ , then an intensity estimate is:

$$\hat{\lambda}_t = \frac{\hat{x}_t}{\tau}$$

**2.1. Theoretical Concepts Underpinning Smart City Data Integration**

Data integration goals and mechanisms are at the forefront of smart city development. The urban research cycle can be viewed as a daisy chain of research questions that are possible to answer only when data are made available to multiple knowledge communities. It encompasses individual research projects at specific city locations and the creation of data ecosystems composed of diverse and heterogeneous data sources and providers. A city-based data ecosystem can be visualized as an expanding network of interconnected data nodes enabling the transfer and sharing of data provenance and knowledge for the benefit of the wider community. The resulting Smart City Decision Support System facilitates the analysis, real-time monitoring, prediction, and verification of the effects of public-policy decisions.

To support integrated data usage for smart city development, data ecosystems must implement data ingestion, enrichment, storage, processing, governance, and management pipelines that address the core challenges of big data analytics. Together with deployment, security, and data-protection considerations, they create a full-stack architecture enabling data fusion. An important aspect of the design is the selection of cloud versus on-premises deployment for each modular component. Containerization and orchestration technologies help achieve cost-effective, scalable, and elastic hybrid cloud solutions capable of supporting both batch- and stream-processing workloads throughout the ecosystem.

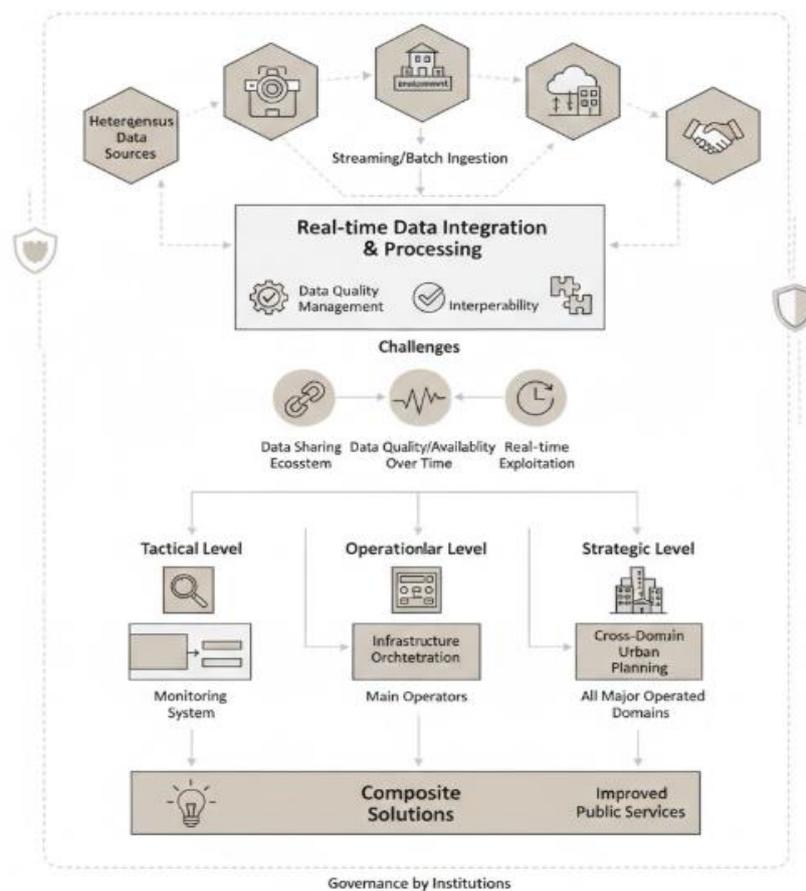
**III. DATA ECOSYSTEMS IN SMART CITIES**

The architecture of data ecosystems is examined, specifically communication pathways of data, data sources, interoperability, data provenance, and the differences between streaming and batch processing. The range of stakeholders that comprise data ecosystems is reviewed, and the usefulness of integrated data for higher-level decision making—especially at the level of infrastructure and service dimensioning—is highlighted.

Data ecosystems comprise the complete set of data sources available to decision makers, spanning real-time feeds, archived records, and information accessible through crowdsourcing and sharing. Data may originate from smart devices, social and web media, service systems, or leveraged from similarly structured non-smart systems. At lower integration levels, such as that of service operations and management, combined data only require synchronization; at higher levels—such as the level of infrastructure dimensioning—demand and supply models must be inferred from the data in order to derive cross-service applications and synergies. Data integrity, security, and provenance therefore become paramount as integrated data strategies evolve toward more ambitious final objectives. Fusion approaches that allow all data sources and types to be harnessed in a uniform manner are under investigation for several key cross-domain application areas.

### 3.1. Integrating Data Streams for Intelligent Urban Solutions

An integrated system architecture guides the organization and connection of information from various data sources to enable intelligent analysis and the development of smart city solutions. Integrated, real-time data in the context of a data ecosystem for urban planning involve several aspects: the integration of heterogeneous data sources, data quality management, the selection of a streaming or batch-processing approach, and the fulfillment of the requirements of the integrated users of the data streams. The availability of streaming data from multiple sources in the urban ecosystem holds great promise to address intelligent urban planning needs and support intelligent solutions. However, the application of these integrated data streams for intelligent analysis does not come without challenges: interoperability of heterogeneous data sources, changes over time in the quality and availability of the data streams, establishment of a data-sharing ecosystem, and the capability to exploit the data streams in real time. Furthermore, smart city data are governed by different types of institutions with separate stakeholders and distinct objectives, ways of data collection, and types of analysis.



**Fig 2: Multi-Tiered Urban Intelligence: An Integrated Architecture for Heterogeneous Real-Time Data Orchestration across Tactical, Operational, and Strategic Planning Domains**

Access to high-quality integrated real-time data is essential for stakeholders at various levels of granularity to make informed decisions that improve the delivery of public services. At the tactical level, real-time data support a broad spectrum of intelligent or smart applications that use information generated by monitoring systems or traditional use of infrastructure. These applications can usually be deployed by end users acting on their own information demand, with low cross-domain information interaction. At the operational level, intelligent real-time information systems seek to monitor and orchestrate infrastructure resource operations, interacting essentially with the main operators of the infrastructure. At the strategic level, the information systems address cross-domain requirements of high-level urban planners, with integrated real-time access to information and intelligence from all the major operated domains. The ability to develop intelligent urban applications uses various types of streams produced by traditional urban monitoring systems, with composite solutions addressing users' needs across multiple domains.



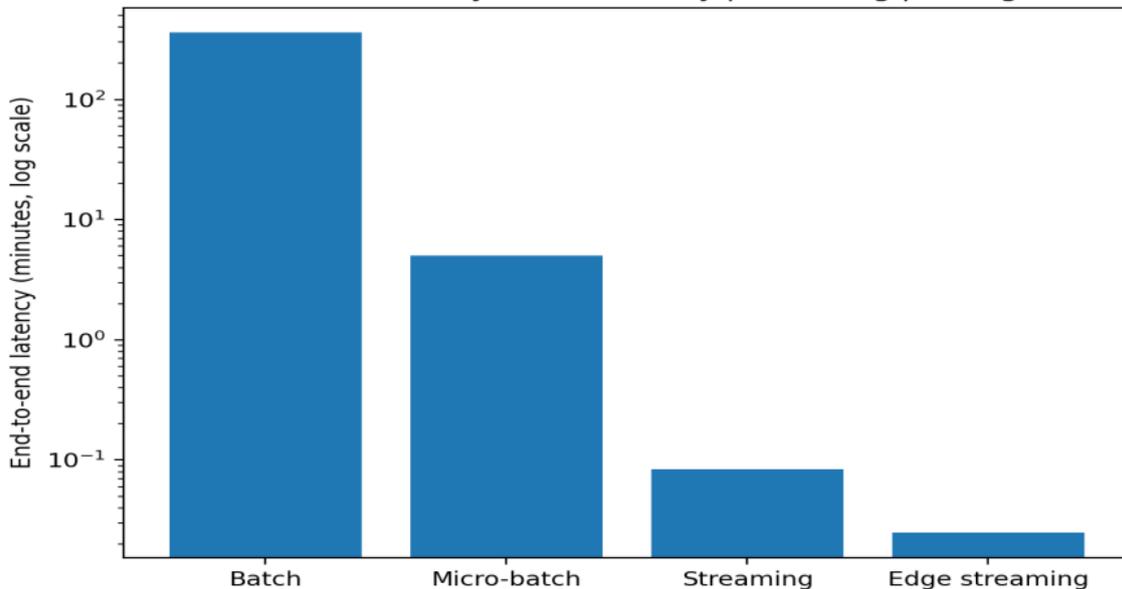
Layer	Typical tech (examples)	Role in paper
Processing	Spark/Flink, stream processors	Support batch+stream pipelines; generate predictions
Serving/Delivery	APIs, dashboards, digital twins	Expose data/products to tactical–strategic users
Governance & Compliance	Metadata catalog, lineage, access control	Ensure quality, provenance, auditability, privacy/regulation

#### IV. HYBRID AI ARCHITECTURES FOR URBAN PLANNING

In smart-city planning processes, multi-agent systems can be organized as federated or edge AI solutions. Federated architectures consist of a central controller receiving knowledge inputs from specialized agents and orchestrating local responses based on global objectives, while collocated agents communicate their local results with one another. Edge-in-AI and Edge-as-AI frameworks embed computing at the edge of the data source, thus enabling real-time decision making on a per-sensor basis. Privacy-preserving approaches allow sensitive personal information to remain on the edges so as not to be extrapolated by central analytics. Federated and Edge AI systems are designed to tackle critical requirements for intelligent management and real-time responsiveness in smart cities and communities, particularly during crises.

Hybrid modeling and simulation combine mechanistic models describing the physical processes in a system with data-driven models capturing the simulation gaps and learning from past events. Scenario runs, often with the use of artificial weather generators for environmental conditions, are necessary for exploring system behavior under uncommon situations, underscoring both the importance of the mechanistic modelling and the limited physical validity of the data-driven components. Therefore, an iterative validation procedure is outlined for such combined ML/DS models, integrating data-driven prediction-error simulations into the conventional scenario analysis of the mechanistic simulation models. The scenario generation phase is supported by the availability of a fine mortality prediction model that can be applied to any location with point-wise weather information.

Illustrative latency differences by processing paradigm



#### Equation 2) Streaming vs batch pipelines: equations for latency and freshness

A practical “decision usefulness” quantity is **data age (freshness lag)** at time  $t$ :

- Let the newest event timestamp already processed be  $t_{last}$ .  

$$DataAge(t) = t - t_{last}$$

End-to-end latency can be decomposed:

$$L = L_{ingest} + L_{process} + L_{serve}$$

Streaming aims to keep  $L$  small; batch often yields large  $L$  but richer computation.



#### 4.1. Federated and Edge AI for Real-time Decision Making

Hybrid AI architectures that can offer cluster-level, regional, and city-wide analytics and prognosis typically comprise two components: a centralised meta-analytical model and a set of federated micro-analytical units distributed at the edges of the data ecosystem. Given the different quality and volume of heterogeneous data produced at diverse spatial and temporal scales, Urban Data Ecosystems can benefit from the incorporation of edge analytics together with centralised model-based strategies. The former leverages data produced by users and devices at the edge of the ecosystem to derive smart responses in near real-time. However, any kind of ordinate decision-making can be enabled only by complementing edge intelligence with a privacy-preserving central data consolidation layer that is able to aggregate and expose useful information for classified decision-making at the city level.

The AI methodology that nourishes edge analytics is called Edge Artificial Intelligence (AI). Edge AI refers to systems that decided and acted upon locally, closer to where the data is generated. Current trends indicate that major AI service providers such as Google, Microsoft, Amazon, Metaverse, Baidu, Alibaba and Tencent are devoting important efforts in the design of proper architectures to boost the development of Edge AI. Such architectures are empowered by advanced data collaboration paradigms, including federated and transfer learning.

#### 4.2. Hybrid Modeling and Simulation

Hybrid modeling and simulation appear in diverse sectors, including energy systems, traffic management, water resources, and health. While mostly considered separately, the integration of mechanistic models with data-driven models is less common and offers important advantages. The application of hybrid modeling to urban planning addresses the growing interest in testing different policies, infrastructures, or technologies before applying them in the urban context. An illustrative case involves a transport scenario using a mechanistic model complemented by a data-driven model that provides additional information for operation and demand. Such integration enables managing the positive and negative effects of transportation matrices considered for the same planning horizon. Moreover, validation improves corresponding estimates when a hybrid approach is adopted. The core concept consists of using a classic transport model augmented with a data-driven approach that avoids losing key information during temporal space reductions.

Combination of mechanistic and data-driven models allows urban planners to conduct future-oriented scenario analyses while also acting as a validation tool. In areas where mechanistic models tend to “forget” some key variables—for instance, individuals' behavior with respect to external influences—support from data-driven extensions strengthens the estimates. However, the challenge remains to determine how to integrate these components. In the proposed methodology, the hybridization takes place during the execution of an ex post validation procedure and is linked to the current state of the art of the models involved. The two branches can be decoupled, allowing for stand-alone usage. When necessary, the ad hoc coupling with a second data-driven extension offers an enriched estimation of the operational variables.

## V. BIG DATA FRAMEWORKS FOR URBAN INFRASTRUCTURE

Big data architectures in urban planning start with data ingestion and proceed through storage, processing, and delivery components. Data ingestion enables the structuring and transfer of data from multiple sources through scalable pipelines for batch processing or online data streaming. Based on the target use cases, pipelines may be implemented in the cloud or in on-premises data centers. Containerized implementations promote deployment and orchestration flexibility, while orchestration tools improve resource provisioning and deallocation according to workload fluctuations.

Ensuring data quality and compliance constitutes a prerequisite for guaranteeing analytic reliability and fostering the acceptance of data use across domains and stakeholders. Data quality control is built on metadata management, tracking of data lineage during ingestion and processing, security controls to govern data access and usage, auditability features to investigate mishandling instances, and alignment with regulatory standards such as the General Data Protection Regulation and the ePrivacy Directive. The creation of a data commons enables well-defined data sharing and reuse following specific guided contracts while safeguarding both individual privacy and collective commons.

#### Equation 3) Federated / edge AI orchestration: objective + FedAvg update

##### 3.1 Global optimization objective

Assume  $K$  edge nodes, node  $k$  has  $n_k$  samples, total  $n = \sum_k n_k$ .

Each node has local empirical loss  $F_k(w)$ . A standard federated objective is:

$$\min_w F(w) = \sum_{k=1}^K \frac{n_k}{n} F_k(w)$$

**3.2 FedAvg update (step-by-step)**

At round  $t$ , the server broadcasts  $w^{(t)}$ .

Each client performs local training (e.g., a few SGD epochs) and returns  $w_k^{(t+1)}$ .

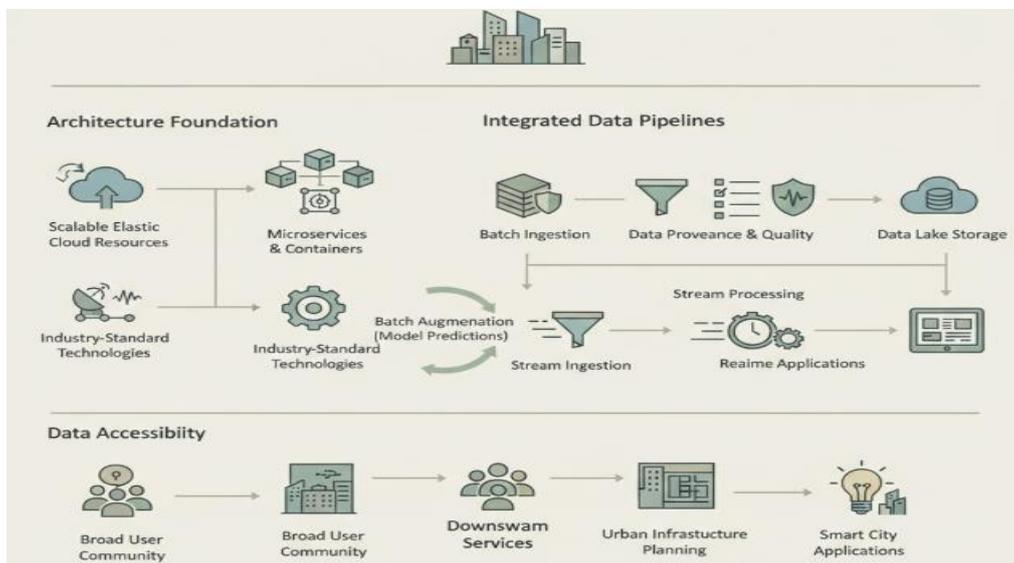
Server aggregates:

$$w^{(t+1)} = \sum_{k=1}^K \frac{n_k}{n} w_k^{(t+1)}$$

**5.1. Data Ingestion, Storage, and Processing Architectures**

Data ingestion, storage, and processing architectures serve as the foundation of Big Data ecosystems for urban infrastructure planning. For an ecosystem to be effective, data from numerous sources must be ingested, stored, processed, and provisioned at scale while remaining accessible to a broad user community. There are two key considerations. First, the data pipeline must be scalable, running on elastic cloud resources that can adapt to changing usage patterns. Second, the architecture must make use of industry-standard technologies and be built as a set of independent microservices running in lightweight containers. Container orchestration tools, such as Kubernetes, can manage the deployment and scaling of these services.

The data ingestion, storage, and processing architecture should support batch and streaming data processing pipelines in a seamless manner. An initial batch of historical data is typically ingested directly from data sources and processed according to the required data providence levels. Subsequently, data is acquired as a continuous stream from data sources in order to be made usable in real-time applications. Data is processed according to the appropriate levels of quality and data provenance before being made accessible to either downstream users or storage services. Batch processes can augment streaming pipelines at different time frequencies with data products, such as model predictions, that are not specified as real-time services.



**Fig 3: Cloud-Native Urban Intelligence: A Scalable Microservices Framework for Integrated Batch and Stream Processing in Smart Infrastructure**

**5.2. Data Quality, Governance, and Compliance**

High-quality data is essential for effective decision making; systematic monitoring and corrective actions are required to ensure the required quality levels. A comprehensive set of data quality attributes have been proposed, covering accuracy, completeness, consistency, timeliness, and believability. Governance is critical for ensuring accountability and oversight, defining who can access, modify, and use data, and establishing policies, standards, and procedures.



Data stewards support governance by managing data quality, ensuring compliance with standards, and documenting data lineage and provenance.

Sufficient metadata must also be maintained to ensure that data can be used in accordance with its prescribed aims. High-quality metadata are needed to establish suitable data for specific tasks. Data lineage tracks the sources and transformations of data elements, enabling auditing, quality control, and troubleshooting. Provenance describes the origins and context of data and contributes to the validation of dataset quality. Metadata also support security controls and auditability, satisfying legal, regulatory, and compliance requirements.

## VI. CROSS-DOMAIN APPLICATIONS IN SMART CITY PLANNING

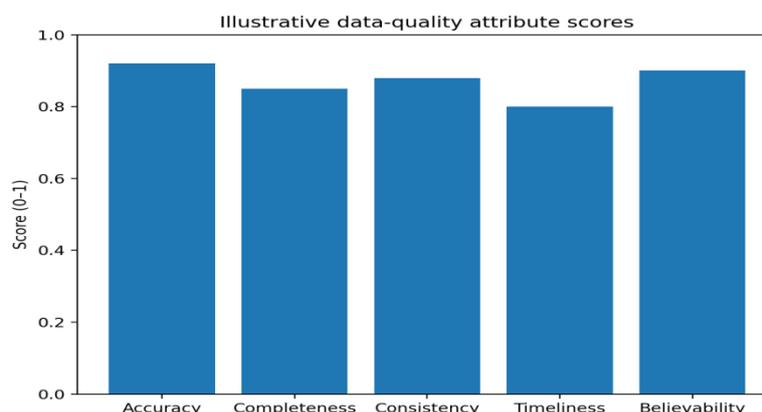
Data-driven frameworks benefit planning in a variety of domains traditionally addressed separately. In transport and mobility, transport data and urban land use data are fused to improve travel demand estimation, e.g., using travel demand modeling to predict the impact of traffic congestion at a regional scale. Intelligent transportation systems create multimodal transport networks where traffic flow at intersections is controlled using automata-inspired decision-making strategies. Traffic prediction models facilitate intelligent transport-related applications such as traffic management, long-distance travelling time estimation, mobile navigational aids, and traffic routing. Transport demand management – achieving a more evolvable transport system through human behaviour change – is another cross-domain application, utilizing dense data streams about people.

Urban energy systems and resilience are also cross-domain topics. Integrating transport systems into energy planning supports demand-response practices, while complete cross-domain approaches allow studying transportation-energy interdependencies. Such complex cross-domain applications are also needed in other sectors to promote resilience. Energy load data are fused with weather data to enhance prediction quality. Hybrid methods combining artificial neural networks and support vector regression have been devised for short-term power load forecasting. Urban and cross-regional energy-system digital-twin applications estimate electricity consumption. Streaming data processing techniques improve prediction stability and accuracy in urban energy demand response. Using big-data technology, models of the smart grid have addressed new challenges due to high penetration of distributed generation.

### 6.1. Transportation and Mobility

Multiple domains must be coordinated to enable the optimization of a smart city ecosystem. The traffic domain plays an important role by directly affecting the entire smart city ecosystem, especially through its impact on energy, mobility, and economic factors. Predicting future traffic conditions is vital for effective short-term traffic signal control and congestion mitigation. Anticipating future traffic demand also supports a variety of urban planning processes, including road layout design, transport infrastructure integration, and transport service development.

The integration of different transport-related systems is increasingly important to enhance city travel. Effective implementation requires the seamless use of multimodal services (e.g., bus, bicycle, taxi), which can be supported by demand-supply equilibrium, demand-pool integration, service-patch connection, or a combination of these approaches. Transport networks are also increasingly exposed to extreme climatic events, making resilience planning essential for maintaining multimodal connections. Coordination of transportation branching, proactive planning of repair and maintenance work, the definition of alternative travel routes, and long-term infrastructure redundancy are all important resilience-supporting elements.





**Equation 4) Data quality + governance: metrics and a single “quality index”**

**4.1 Attribute metrics (typical operational definitions)**

**Completeness**

- Let  $M$  be total required fields across records, and  $M_{filled}$  non-missing:

$$C_{comp} = \frac{M_{filled}}{M}$$

**Consistency**

- Let  $V$  be total constraints (schema rules, range rules, cross-field rules) checked,  $V_{ok}$  passed:

$$C_{cons} = \frac{V_{ok}}{V}$$

**Timeliness**

- For records  $i = 1..N$ , with acceptable lag  $T_{max}$ , and actual lag  $\Delta t_i$ :

$$C_{time} = \frac{1}{N} \sum_{i=1}^N \max\left(0, 1 - \frac{\Delta t_i}{T_{max}}\right)$$

**Accuracy**

- If ground truth exists for a sample of size  $N$ , with errors  $e_i = y_i - \hat{y}_i$ :

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N e_i^2}$$

(then map to a 0–1 score if desired)

**4.2 One combined “Data Quality Index” (DQI)**

Choose weights  $w_j \geq 0$ ,  $\sum w_j = 1$  for each attribute score  $s_j \in [0,1]$ :

$$DQI = \sum_j w_j s_j$$

**6.2. Energy Systems and Resilience**

Data from smart cities and control areas can support load forecasting with higher accuracy because hybrid AI architectures allow edge machines closer to the data sources to run machine-learning models at a larger scale, even in privacy-preserving modes. For example, training data can be obfuscated with differential privacy before being sent to a central server, where the accuracy of the prediction model can be carefully monitored. If model accuracy drops below a pre-specified threshold, the central server can issue demand-response signals to the stakeholders.

Integrated data from smart cities and control areas can help improve the resilience of electric power systems to extreme weather. When planning new elements for electric power infrastructure, probabilistic models of extreme events can capture the spatial dependence of failures and restoration times, while data from adjacent cities can complement limited historical information. Well-structured data can also make targeted investment more efficient. Training a supervised model with historical failures and repairs helps direct additional investments to the most vulnerable components, while incorporating investment decisions as a constraint in a rolling horizon formulation suggests the infrastructure expansion enabling the largest improvement in overall resilience.

Data from smart cities and control areas can even help with the planning of sustainable electric power infrastructure. Mechanistic and data-driven models reproduce the main features of both subsystems, and support scenario generation in a realistic space. The state of the sustainable infrastructure depends on climate policies in the control area and on energy-efficiency measures in the smart city. A proper trade-off identifies the relative importance of the two subsystems by quantifying their impact on global costs.

**VII. CONCLUSION**

Future research directions and opportunities for innovation in the application of smart city planning frameworks, and urban decision making. Research captures opportunities for methodological advances in data management and simulation-optimization to address functional requirements and provide balanced policy support.



Integration of large hybrid AI and big data frameworks promises expanded applications for urban ignition heat mitigation, energy, mobility, resilience, transportation, and delivery planning. Cross-domain strategies, novel data sources not yet leveraged in smart city planning, and detailed decision processes warrant further consideration. Urban servicing demand prediction accuracy is essential for electricity grid long-term sustainability and climate commitments. Addressing spatio-temporal-mobility complexification reduces management costs and enhances resilience. Supply-demand-disruption sensing capabilities using crowdsourced information promise planning of transport alternative systems. Traffic forecasting, real-time multimodal demand response delivery directly supported by switching infrastructure availability and sensing information, together with adaptation factors, enhance the urban delivery system's resilience. AI and Big Data, Automated Urban Infrastructure, Passive, Clean Energy.

The proposed frameworks encapsulate the scientific foundations for integrated frameworks based on hybrid AI and large data adopting participatory processes for smart city planning. The open issues identified also create unique, innovative opportunities for scientific, on-line, survey and business-involved planning, opening the door to systematic comprehensive immediate actions addressing heat ignition preparedness through structural and supply-facility evolution, including the realisation of AI predictive capabilities during transport system demand and offer basing process.

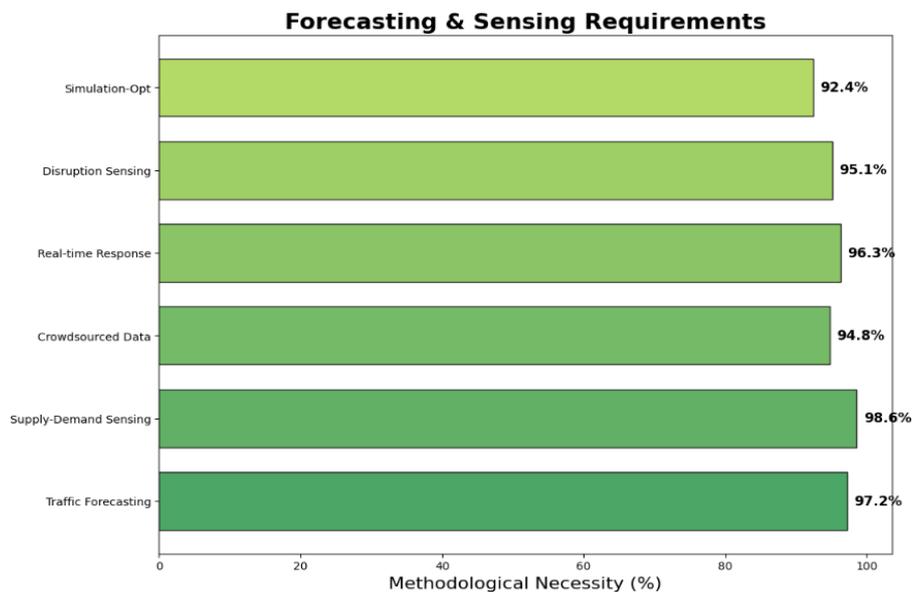


Fig 4: Forecasting & Sensing Requirements

### 7.1. Future Directions and Research Opportunities

Research on smart cities, transport systems, and urban development issues is active in many fields and at different spatial and temporal scales. Therefore, the integration of multidisciplinary research is important because most domain-specific models have a limited field of application. A Hybrid AI and Big Data Framework enables a systematic approach to data fusion and integrated analytics that can be extended to other domains for Smart City Infrastructure Planning. Gaps identified in the literature can serve as a roadmap for research directions and opportunities. Resilience issues, data quality, provenance, security and privacy attribution, integration processes, and requirements on data ingestion, storage, and processing for reliable machine learning remain largely explored.

Interestingly, machine learning has limited capability to discern infrastructure resilience. The prediction of future infrastructure conditions is often performed by human-defined statistical relations, causal and agent-based models. Yet, the ability of machine learning to adapt to changes in surrounding data is useful in embedded systems and edge environments. A Hybrid AI architecture that combines Cloud and Edge/Embedded applications, Federated Learning, Homomorphic Encryption, Secure Multi-Party Computation, Transfer Learning, and Zero-Shot Learning addresses privacy concerns—particularly sensitive for Smart City environments populated by heterogeneous connected devices—and provides the technical framework for multimodal applications based on Human Data. Combining Chemical Kinetics, Transport models, and Transport Prediction provides alternative simulation engines for scenario analysis.



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