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# A Conceptual Framework for Cognitive Digital Twins in Urban Waste Management

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## Abstract

Urban waste management remains a persistent challenge for smart city initiatives, which largely rely on reactive and correlation-based decision support systems. This study proposes a conceptual framework for Cognitive Digital Twins (CDT) in urban waste management that aims to support causal reasoning and adaptive governance. The framework integrates sensing, simulation, causal inference, learning, and human oversight within a unified architecture designed to represent urban waste dynamics as an evolving system. The proposed architecture consists of five functional layers: a sensor and actuator layer for real-time data acquisition, a dynamic simulation layer representing the urban waste system, a causal reasoning layer for diagnosis and counterfactual analysis, a learning layer based on multi-agent reinforcement learning for adaptive policy exploration, and a human interaction layer ensuring transparency and supervisory control. Within this framework, non-parametric Bayesian networks can be applied to identify latent socioeconomic and temporal drivers of waste generation and to construct a structural causal representation of urban waste processes. The learning layer is intended to explore cooperative and adaptive collection strategies under multiple objectives related to efficiency, equity, and service reliability. While empirical validation remains a future step, conceptual analysis and reference to prior literature suggest that the framework has the potential to improve operational understanding and support more adaptive management strategies. Beyond methodological considerations, the framework highlights key governance aspects, including interpretability of algorithmic decisions, alignment of optimization objectives with public values, and the role of human supervision in autonomous urban systems. The findings suggest that CDTs can provide a structured approach for integrating causal modeling and adaptive learning into urban waste management while supporting accountable and participatory governance.

**Keywords:** Cognitive digital twin, Causal artificial intelligence, Multi-agent reinforcement learning, Urban waste management, Structural causal model.

## 1 | Introduction

Urban systems can be understood as complex metabolic processes involving continuous flows of resources and the generation of waste. Rapid urbanization, changing consumption patterns, and increasing environmental pressures have intensified the challenges associated with managing these flows, particularly in the context of Municipal Solid Waste (MSW). Despite decades of technological and organizational innovation,

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MSW management remains one of the most resource intensive and operationally constrained components of urban infrastructure, with persistent inefficiencies in collection, routing, and service reliability.

Recent advances in smart city technologies, including the widespread deployment of Internet of Things (IoT) sensors, vehicle telematics, and open urban data platforms, have significantly increased the availability of real-time operational data for waste management systems. These developments have enabled more responsive monitoring of bin fill levels, vehicle positions, and traffic conditions, and have supported the adoption of dynamic routing and scheduling methods. However, existing data-driven approaches are predominantly designed to detect and respond to observable system states rather than to explain or anticipate them. As a result, most current optimization strategies remain reactive, adjusting collection operations in response to immediate indicators such as container capacity thresholds or congestion levels [1].

This reliance on correlation-based decision support limits the capacity of urban waste management systems to adapt to structural changes in waste generation driven by socioeconomic, spatial, and temporal factors. While predictive models have been introduced to forecast demand, they often operate as black box estimators and provide limited insight into the causal mechanisms that shape waste production and service dynamics. Consequently, there is a growing recognition in the literature that effective urban waste governance requires not only improved sensing and optimization but also integrative frameworks capable of representing system behavior, reasoning about causal relationships, and supporting adaptive decision making under uncertainty [2–4].

Such reactive and correlation-based approaches are poorly aligned with the complex and adaptive nature of urban systems. Cities function as socio-technical systems in which human behavior, economic activity, infrastructure performance, and environmental conditions interact through nonlinear and context-dependent mechanisms. Empirical studies have shown that variations in waste generation and service demand are shaped not only by immediate operational factors, but also by broader socioeconomic, spatial, and temporal drivers, including land-use patterns, mobility dynamics, and event-related population fluctuations [5], [6].

Conventional smart city platforms typically rely on statistical control methods and regression-based forecasting models that prioritize short-term prediction accuracy over explanatory insight. While these methods can capture surface regularities in historical data, they provide limited capacity to represent underlying generative processes or to distinguish causal relationships from spurious correlations. As a result, observed deviations are often treated as random disturbances rather than as manifestations of structural changes in urban activity patterns.

This limitation has important implications for system performance and equity. Optimization strategies derived from purely correlation-based models tend to focus on locally observable efficiencies, such as minimizing travel distance or response time, without accounting for longer-term adaptive behavior or feedback effects. Such strategies may improve operational metrics in high-density or data-rich districts while leaving peripheral or socially vulnerable areas underserved, thereby reinforcing existing spatial inequalities.

These challenges indicate that the concept of the Digital Twin in urban waste management requires a conceptual extension beyond real-time monitoring and predictive analytics. Rather than functioning primarily as a high-resolution visualization or control interface, a Digital Twin can be framed as a computational model capable of supporting causal analysis and scenario exploration. By linking observational data with mechanistic representations of system dynamics, such a model can move from describing what is happening to examining why it is happening and how interventions may influence future system states.

Within this context, the role of the Digital Twin in urban management warrants reconsideration. Existing implementations of Digital Twins in smart city applications primarily function as high-fidelity virtual representations of physical assets and processes, supporting monitoring, visualization, and short-term forecasting. While such models enhance situational awareness, they largely remain descriptive in nature and depend on correlation-based analytics to relate observed variables. As a result, most Digital Twins operate as reactive simulation environments rather than as systems capable of interpreting or explaining the dynamics they reproduce [7].

A conceptual shift is therefore required from viewing the Digital Twin as a passive replica of urban infrastructure to framing it as a cognitively enabled system. In this perspective, a Digital Twin is endowed with an internal model of the system it represents, capturing not only observable states but also the causal mechanisms that generate them. For urban waste management, this implies moving beyond the representation of container fill levels or vehicle trajectories toward modeling the underlying drivers of waste generation and service demand, including demographic characteristics, land use patterns, mobility flows, and temporal activity cycles [8].

Such a cognitively oriented Digital Twin must be capable of causal reasoning and counterfactual analysis. By integrating probabilistic causal models, the system can infer likely explanations for observed variations in waste generation and evaluate alternative intervention strategies under hypothetical conditions. These capabilities enable the transition from merely reacting to operational signals toward anticipating system behavior and exploring the consequences of policy choices before their implementation. In this sense, the Digital Twin becomes not only a tool for operational optimization but also a computational environment for structured experimentation and learning [9–12].

Endowing Digital Twins with these capabilities provides a pathway toward overcoming the limitations of correlation-based optimization and supports the development of more adaptive and interpretable decision support systems. Rather than reinforcing a cycle of short-term reactive adjustments, a cognitively enabled Digital Twin can contribute to predictive and prescriptive forms of urban governance by linking data streams with causal understanding and policy-oriented simulation.

Developing a cognitively enabled Digital Twin for urban waste management requires the integration of methodological perspectives that extend beyond conventional urban informatics and systems engineering. Such an approach draws on concepts from complex systems theory, causal machine learning, behavioral and socioeconomic modeling, and agent-based simulation. The central challenge lies in designing an architecture capable of learning and updating an internal representation of urban waste dynamics from heterogeneous, noisy, and partially observed data sources, while preserving interpretability and supporting human oversight in operational and policy contexts.

MSW management provides a suitable application domain for examining this integration, as it involves well-defined material flows, substantial economic and environmental externalities, and strong interactions between infrastructure performance and human behavior. These characteristics make it a relevant context for exploring how causal modeling and adaptive learning can be embedded within a unified digital representation of an urban service system [13–15].

This study addresses this challenge by proposing a conceptual framework for a Cognitive Digital Twin (CDT) that combines causal inference, simulation, and adaptive decision support within a structured architecture. The paper first outlines the functional layers of the proposed framework and their interactions. It then discusses the computational methods that support causal reasoning and adaptive policy exploration. Finally, it examines the governance and ethical considerations associated with the deployment of such systems in public service management, including transparency, accountability, and the role of human supervision.

This study proposes a conceptual framework for a CDT in urban waste management, emphasizing the integration of causal inference, simulation, adaptive learning, and human oversight. The framework is positioned as a tool for understanding urban waste dynamics, identifying structural drivers of waste generation, and supporting policy exploration, rather than as a summary of operational outcomes. The architecture comprises functional layers for sensing, simulation, causal reasoning, adaptive learning, and human interaction, each enabling analytical and decision-support capabilities. By situating the CDT within the broader context of complex urban systems, this study highlights its potential to bridge gaps in traditional, reactive, correlation-based approaches. The following sections outline the conceptual design of the CDT, discuss the computational methods that enable causal reasoning and adaptive policy exploration, and address governance considerations, including interpretability, accountability, and the role of human oversight.

## 2 | A Five-Layer Architectural Framework for the Cognitive Digital Twin

The development of a CDT for urban waste management requires an architectural foundation that is both methodologically rigorous and conceptually grounded in theories of complex and adaptive systems. Urban service systems operate through tightly coupled interactions between physical infrastructure, human behavior, and institutional decision processes, which cannot be adequately represented through monolithic or purely data-driven models. Consequently, an effective architecture must distinguish between key functional roles, including data acquisition, system representation, causal analysis, adaptive policy generation, and human supervision, in order to support modularity, interpretability, and controlled system evolution [16].

In this study, a five-layer architectural framework is proposed to structure these roles within an integrated yet analytically separable system. *Fig. 1* illustrates the proposed five-layer architectural framework of the CDT for urban waste management, integrating perception, simulation, causal inference, strategic autonomy, and human oversight. The framework organizes sensing and actuation, dynamic system simulation, causal reasoning, adaptive learning, and human interaction as distinct but interdependent layers, enabling information to circulate through a closed cognitive loop of perception, inference, decision support, and feedback. Such a layered design aligns with established principles in cyber-physical systems and digital twin research, where separation of concerns facilitates scalability and the incorporation of heterogeneous data sources and analytical models. By explicitly embedding causal and learning components within this layered structure, the proposed architecture is intended to move beyond descriptive system mirroring toward an analytical representation capable of supporting explanation-oriented and policy-relevant reasoning about urban waste dynamics [17–19].

**Stratum 1.** Phenomenological layer (system perception and actuation).

The first stratum operationalizes the interface between the CDT and the physical urban environment by supporting structured system perception and controlled actuation. Rather than functioning as a conventional IoT layer, this stratum is conceived as a heterogeneous sensing and actuation ensemble capable of capturing multiple dimensions of urban waste processes. Smart collection points may incorporate sensing modalities that extend beyond volumetric fill-levels to include indicators of material composition and compaction state, while collection vehicles can be regarded as mobile observation units integrating positioning data, load measurements, and situational awareness signals relevant to service conditions.

In addition to waste-specific measurements, this stratum is designed to accommodate contextual urban signals that influence waste generation and collection dynamics. These may include traffic conditions, meteorological variables, scheduled public events, and aggregated mobility indicators, which together provide situational context for interpreting localized waste observations. The role of this layer is not limited to data transmission but includes preliminary data structuring and harmonization functions, such as temporal synchronization, spatial referencing, and basic quality assessment.

The output of the phenomenological stratum is therefore not a collection of isolated sensor readings but a coherent stream of time- and location-indexed observations enriched with descriptive metadata. This representation establishes a consistent perceptual substrate for higher layers of the architecture, enabling subsequent processes of system modeling, causal analysis, and adaptive decision support to operate on a unified and interpretable view of urban waste dynamics.

**Stratum 2.** Dynamic simulation layer (system world model).

Building upon the perceptual substrate established in the phenomenological layer, the second stratum provides the internal world model of the CDT through a dynamic simulation environment. This layer is conceived not as a single monolithic simulator but as a coordinated ensemble of complementary modeling paradigms that together approximate key structural and behavioral aspects of the urban waste system. Its purpose is to offer a computational representation of urban waste dynamics that supports analysis, prediction, and policy exploration under varying contextual conditions.

The simulation environment integrates multiple model classes, including spatial representations of the built environment, agent-based formulations of population behavior and collection activities, and process-oriented models of logistical operations such as routing and facility throughput. In addition, simplified physical abstractions may be used to represent factors such as equipment utilization, compaction behavior, and resource consumption. This multi-model configuration enables the system to capture interactions between infrastructure constraints, human activity patterns, and operational decision processes without relying on a single modeling formalism.

A defining characteristic of this layer is its treatment as an adaptive and continuously updated representation rather than a static digital replica. Incoming observations from the phenomenological layer are incorporated through probabilistic synchronization mechanisms, allowing the simulation state and selected model parameters to be iteratively adjusted in light of new evidence. In this sense, the simulation functions as a maintained hypothesis about the evolving urban system, rather than as a fixed predictive engine [20], [21].

By supporting the parallel evaluation of alternative operational assumptions and intervention scenarios, the dynamic simulation layer enables the exploration of plausible system trajectories under different policy options, environmental conditions, and demand patterns. These scenario-based projections provide an intermediate analytical substrate for higher layers concerned with causal reasoning and adaptive decision support, linking real-time system perception with forward-looking system understanding.

**Stratum 3.** Causal-inferential layer (diagnostic and explanatory reasoning).

The third stratum constitutes the cognitive transition from observation and simulation to causal understanding within the CDT. This layer is responsible for the discovery of structural relationships among urban waste system variables and for real-time inferential reasoning. Its primary function is to transform raw and simulated data streams into analytically interpretable causal knowledge that can inform adaptive decision-making. The causal-inferential layer operates on multiple temporal scales. On a slower, periodic basis, such as weekly or monthly intervals, a Causal Discovery Engine processes historical data from both the physical city and the simulation layer.

Advanced computational techniques, including gradient-based neural causal models and constraint-based methods like the PC algorithm, are applied to infer the underlying structure of a Structural Causal Model (SCM). In this representation, nodes correspond to system variables (e.g., public holidays, pedestrian flow in specific districts, commercial bin fill rates, collection vehicle delays) and edges denote direct causal influences quantified through conditional probabilities. In parallel, a Real-Time Inference Engine leverages the learned SCM to perform online reasoning. When deviations or anomalies are detected, such as unexpectedly rapid bin fill events, the engine applies abductive inference to generate the most probable causal explanations. These insights are fed back into the simulation layer, updating predictive models and enabling scenario exploration. By integrating structural causal understanding with real-time inferential feedback, this layer elevates the digital twin from a reactive observational tool to a diagnostic and explanatory partner, capable of addressing questions of "why" and "what if" in urban waste management.

**Stratum 4. Strategic autonomy layer (multi-agent decision-making)**

At the apex of the CDT architecture lies the strategic autonomy layer, where adaptive decision-making intelligence operationalizes the insights derived from perception, simulation, and causal reasoning. This stratum is implemented as a Multi-Agent Deep Reinforcement Learning (MADRL) system, in which a population of artificial agents represents potential decision strategies for individual collection vehicles, fleet managers, or other operational units within the urban waste system. Agents are trained entirely within the dynamic simulation environment of the second stratum, iteratively exploring action spaces and learning policies through reinforcement signals. The reward function guiding learning encodes multiple city priorities, including operational efficiency, environmental impact, coverage, service reliability, and equity constraints. Unlike single-agent optimization, the MADRL framework promotes interaction among agents, allowing implicit coordination, resource-sharing, and division of labor to emerge as adaptive strategies for system-level performance.

Once trained, these agents are capable of prescribing operational actions such as dynamic routing, dispatch scheduling, and depot resource allocation, which are first evaluated within the simulation environment to ensure consistency and robustness before being applied to physical actuators in the phenomenological layer. In this way, the strategic autonomy layer closes the cognitive loop, translating predictive insights and causal understanding into coordinated, adaptive, and policy-aligned interventions in the urban waste system. By integrating multi-agent learning with the preceding layers of perception, simulation, and causal inference, this stratum exemplifies the capacity of the CDT to support autonomous yet accountable urban management.

**Stratum 5.** Human oversight and governance layer (cognitive stewardship interface).

Encompassing all preceding strata, the final layer ensures that the CDT functions as a tool for augmented intelligence rather than a replacement for human judgment and democratic accountability. This layer provides municipal operators and decision-makers with interpretable visualizations of the SCM, along with transparent explanations of the rationale behind agent decisions and learned policies. A central component of this layer is the Metacognitive Orchestrator, which continuously monitors system performance, balances the trade-off between exploratory simulations and the exploitation of proven strategies, and can initiate alerts or learning resets when necessary. By structuring human interaction around clear oversight mechanisms, this layer operationalizes a human-in-the-loop paradigm in which policymakers, ethicists, and operators maintain active control over system behavior.

Human agents can set high-level objectives such as ensuring equitable service coverage or meeting predefined efficiency targets while also auditing the reward structures used by learning agents to detect and correct potential biases. Operators retain unambiguous authority to override automated decisions, ensuring that accountability and ethical governance are preserved. In doing so, the Human Oversight and Governance Layer formally anchors the CDT within a framework of responsible urban stewardship, reinforcing the principle that ultimate responsibility for city management remains with human actors while the digital twin extends their cognitive and operational reach [22].

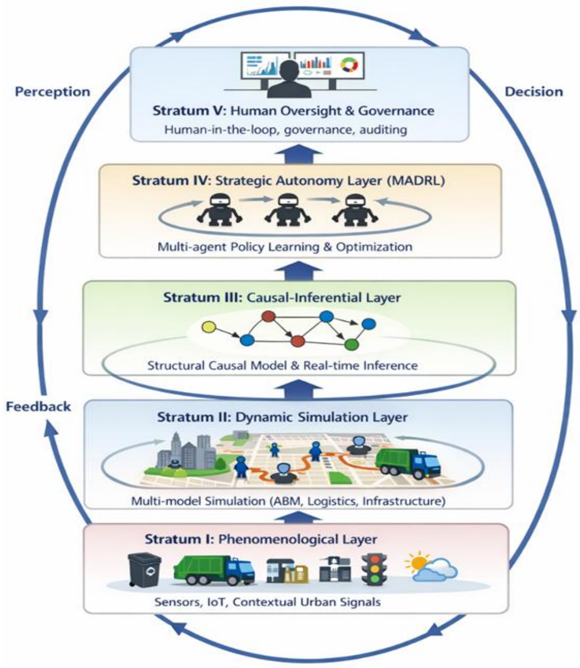


**Fig. 1. Five-layer CDT architecture for urban waste management; closed-loop integration of sensing, simulation, causal reasoning, autonomous decision-making, and human oversight.**

# 3 | Algorithmic Core: Causal Discovery and Multi-Agent Autonomy

The theoretical five-strata architecture is operationalized through an algorithmic core that integrates two complementary branches of artificial intelligence: causal machine learning and multi-agent reinforcement learning. This integration is schematically illustrated in *Fig. 2*, which depicts the closed-loop interaction between causal inference, dynamic simulation, and multi-agent learning within the CDT. This core translates the conceptual framework into actionable insights and adaptive operational policies for urban waste management. Causal discovery begins with the aggregation of high-dimensional, longitudinal datasets spanning weeks, months, or years, incorporating diverse variables from the phenomenological layer. Unlike conventional time-series analysis, which primarily seeks predictive correlations, this process is explicitly oriented toward uncovering directed causal relationships. A Non-Parametric Bayesian Network approach is employed, avoiding assumptions about predefined graph structures or linear dependencies. Techniques such as the Dirichlet Process Mixture Model (DPMM) enable the automated inference of latent states and the identification of complex, indirect interactions among system variables. For example, the system may determine that "Weekend Sunshine Hours" does not directly cause an "Increased Park Bin Fill-Rate," but rather activates a latent variable representing "Leisure Activity Levels in Green Spaces," which in turn exerts causal influence on "Park Waste Generation" and separately affects "Traffic Congestion Around Parks," ultimately impacting "Collection Truck Access Time." Such granular, non-parametric modeling is crucial for capturing the nuanced, often indirect causal pathways that define urban socio-technical ecosystems, providing a structured foundation for adaptive multi-agent policy learning in subsequent layers [23–25].

Once an SCM has been inferred, it becomes the core logic linking causal understanding with the dynamic simulation environment. In this role, the SCM not only represents the relationships between system variables but actively governs the behavior of the simulation, ensuring that forecasts account for probabilistic causal dependencies rather than relying solely on historical trends. By embedding these causal relationships, the CDT can generate a rich spectrum of plausible future scenarios, each annotated with its causal lineage. This approach allows planners and operators to understand not only what is likely to occur, but why it occurs, providing a foundation for risk-aware and informed decision-making [26].

Beyond predictive capabilities, the SCM enables systematic exploration of hypothetical interventions. By selectively adjusting causal pathways or "cutting" specific connections within the model, the system can simulate counterfactual scenarios, allowing stakeholders to examine the potential effects of alternative policies or operational strategies without impacting the real-world system. For instance, the effect of a temporary restriction in park access or the introduction of a new waste collection schedule can be evaluated computationally before implementation, highlighting both direct and indirect consequences.

The integration of causal inference with dynamic simulation establishes a structured framework for policy exploration that is grounded in the actual drivers of system behavior. The integration of causal inference with dynamic simulation transforms the CDT from a purely predictive instrument into an interactive, decision-support platform, capable of evaluating multiple futures that are informed by causal understanding, adaptive learning, and probabilistic reasoning. By maintaining explicit representation of causal pathways and their uncertainties, the CDT allows urban planners to test strategies, anticipate emergent system responses, and design interventions that are both resilient and evidence-based.

Concurrently, the CDT operationalizes adaptive decision-making through an MADRL system. Each agent in the collective operates under a Partially Observable Markov Decision Process (POMDP) framework, perceiving only a localized view of the city state, such as nearby bin statuses, vehicle fuel levels, and immediate traffic conditions, while learning to make optimal decisions in a complex, interconnected environment. The objective of each agent is to acquire a policy, $\pi$, that maps observations to actions (e.g., move, collect, wait, return to depot) to maximize cumulative expected reward.

The distinguishing feature of this layer is the combination of a multi-agent context with a sophisticated, multi-objective reward structure. A Centralized Training with Decentralized Execution (CTDE) paradigm is employed, enabling agents to learn cooperative strategies such as dynamic territory allocation or load balancing without explicit programming. During training, a central critic network evaluates the joint performance of all agents, providing guidance to individual actors. The guidance provided by the central critic network facilitates emergent coordination, allowing the collective to optimize global system objectives while each agent responds to local conditions.

Reward functions are designed to balance operational efficiency, service reliability, and fairness, translating urban policy priorities into agent incentives. This framework ensures that the CDT does not merely predict outcomes but actively learns adaptive, cooperative, and policy-aligned strategies that can be validated within the simulation before deployment in real-world operations. By integrating multi-agent reinforcement learning with the causal and simulation layers, the system achieves a closed-loop of continuous learning, adaptive planning, and risk-aware decision-making in urban waste management.

The synergy between the SCM and the MADRL agents represents the core adaptive capability of the CDT. Importantly, the SCM does not prescribe specific actions to the agents; rather, it shapes the environment in which they learn and adapt. By generating realistic and causally coherent simulation scenarios, including rare events, anomalies, and system disruptions, the SCM ensures that agents are exposed to a diverse and challenging set of conditions, preparing them to respond robustly to novel situations that may not be represented in historical data.

For instance, an agent trained solely on past operational data might fail to anticipate the impact of an unusual urban festival or sudden infrastructure constraint. In contrast, when such events are causally generated within the simulation based on factors like cultural calendars, weather patterns, and human mobility, agents encounter analogous conditions during training and can learn effective adaptive strategies [27].

Moreover, the causal insights produced by Strata III serve to guide and constrain agent exploration. If the causal inference engine identifies that recurring service disruptions in a district are primarily due to persistent traffic congestion at a key intersection, the reward functions for agents operating in that area can be temporarily adjusted to penalize routes through the congested location. The causal adjustment of agent reward functions encourages agents to discover alternative paths and strategies, enhancing the robustness and efficiency of their learned policies [28].

This interaction establishes a continuous feedback loop: causal understanding informs the design of challenging and realistic training environments, leading to improved agent policies, whose outcomes subsequently generate new data to refine and update the SCM. In this way, the CDT achieves a self-reinforcing cycle of learning, adaptation, and policy improvement, bridging causal inference and operational decision-making in a dynamic urban environment [29].

Operationalizing the CDTs algorithmic core demands a robust computational infrastructure capable of supporting both causal discovery and continuous multi-agent learning. The training of MADRL agents and the inference of SCMs are conducted offline on high-performance computing platforms, where the simulation core generates extensive synthetic experience to expose agents to a wide range of plausible urban scenarios. Once trained, the agent policies and the updated causal graph are deployed to the live operational environment, where lightweight inference engines and policy execution modules operate in near real-time, translating the CDT's insights into actionable guidance for urban waste management.

This hybrid training-deployment paradigm ensures that the system remains dynamic and continually evolving. Each day of real-world operation generates new observations, which are assimilated into the causal and learning layers. These data periodically inform the retraining and refinement of both the SCM and agent policies, allowing the CDT to adapt to long-term changes such as urban growth, seasonal patterns, or shifts in citizen behavior. By continuously integrating fresh evidence and re-evaluating policy performance, the CDT maintains its effectiveness, relevance, and responsiveness over time.

Ultimately, this approach establishes a self-reinforcing loop of learning, adaptation, and operational deployment, ensuring that the CDT functions not as a static tool but as a living, continuously improving system that bridges predictive analytics, causal understanding, and autonomous decision-making in complex urban environments.

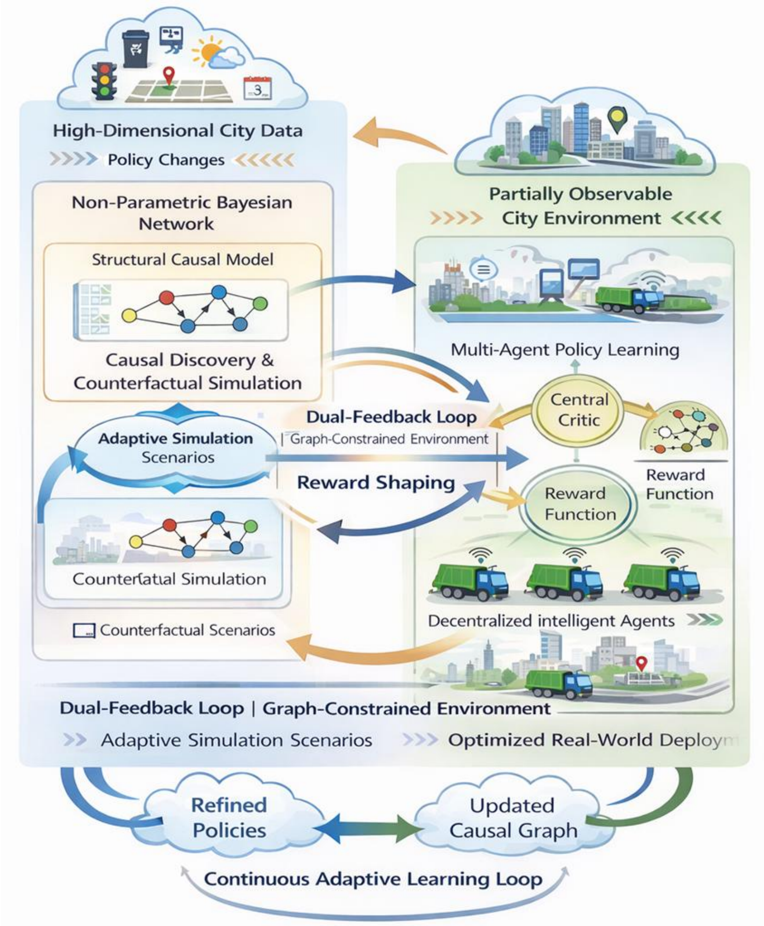


**Fig. 2. Algorithmic core of CDT; closed-loop interaction among causal discovery, SCM, dynamic simulation, and MADRL.**

Causal relationships inferred from urban data shape the simulation environment, which generates scenarios for training cooperative agents under a CTDE scheme. Operational data continuously updates both the causal model and agent policies, enabling adaptive and risk-aware urban waste management.

# 4 | Simulation-Based Validation of the Proposed Framework

To examine the feasibility and analytical potential of the proposed CDT framework, a high-level simulation environment was constructed to represent the metabolic behavior of a stylized urban district. Rather than functioning as a conventional logistics or traffic simulator, this environment was designed as an integrated synthetic urban system capable of reproducing interdependent social, environmental, and operational processes relevant to municipal waste management. The main components of the simulation environment and the proposed CDT framework are summarized in *Table 1*, illustrating their roles, inputs, outputs, and key functionalities. The simulation framework incorporates multiple interacting components. A socio-behavioral module represents household activities, commercial operations, and pedestrian movement based on generalized demographic and land-use patterns. Waste generation is modeled as a stochastic outcome of these activities, influenced by latent drivers such as temporal rhythms, local economic conditions, and contextual urban events. A logistical module emulates collection operations, including vehicle movement, routing constraints, and depot interactions, while an exogenous component introduces contextual disturbances such as weather variability, mobility disruptions, and public calendar effects. To support the assessment of causal learning mechanisms, the underlying waste generation dynamics within the simulation are governed by a predefined causal structure specifying dependencies among behavioral, environmental, and operational variables. This structure remains unknown to the learning components of the framework and serves solely as a reference for evaluating whether the proposed causal inference processes are capable of identifying meaningful relationships from observational and simulated data streams. Within this synthetic yet structured setting, the proposed framework can be examined under controlled but realistic conditions, enabling the interaction between sensing, simulation, causal modeling, and adaptive learning to be explored without reliance on proprietary or incomplete municipal datasets. Accordingly, the objective of this simulation-based evaluation is not to replicate a particular city, but to provide a reproducible and analytically transparent context in which the internal coherence, learning behavior, and governance-relevant properties of the CDT can be investigated.

For comparative assessment, the proposed CDT was examined alongside several representative baseline strategies commonly discussed in the literature on urban waste collection. These reference approaches reflect a spectrum of prevailing practices, ranging from static scheduling policies to adaptive routing mechanisms based on local fill-level thresholds and model-based predictive controllers.

Within the synthetic evaluation setting, the CDT was exposed to the same operational conditions as these baseline strategies, allowing their qualitative behaviors to be contrasted under identical environmental dynamics. The causal discovery component of the framework was applied to an initial segment of simulated observations in order to infer dependencies among behavioral, environmental, and operational variables. The resulting causal structure exhibited substantial correspondence with the predefined generative mechanisms of the simulation, including relationships that were not directly observable from simple correlations, such as indirect links between patterns of human activity and temporal variations in residential waste generation.

In parallel, the multi-agent learning component was trained within the evolving simulation environment, where agents were repeatedly exposed to diverse operating conditions and contextual disturbances. Through this process, adaptive collection policies emerged that differed in structure from rule-based or purely predictive controllers, reflecting sensitivity to both operational constraints and higher-level causal regularities embedded in the simulated system.

Rather than serving as a definitive performance comparison, this benchmark-oriented evaluation is intended to illustrate how the proposed framework can be situated relative to established control paradigms. The emphasis is placed on the ability of the CDT to integrate causal modeling with adaptive decision-making in a unified architecture and to exhibit qualitatively distinct behavioral responses when confronted with complex and context-dependent waste generation dynamics.

The comparative analysis indicated consistent qualitative differences between the proposed CDT and the reference strategies. Across the simulated operational setting, the CDT exhibited lower overall routing intensity and more stable collection patterns relative to rule-based and model-predictive approaches. These differences were reflected in reduced operational burden and more regular service outcomes, suggesting improved coordination between demand patterns and collection decisions.

In addition to efficiency-related behavior, the CDT showed greater robustness under constrained operating conditions. When the system was exposed to scenarios involving reduced resource availability, its adaptive policies adjusted collection strategies in a way that limited degradation in service regularity. In contrast, baseline approaches displayed higher sensitivity to such constraints, with more pronounced disruptions in collection timing and bin availability.

From a distributional perspective, the CDT also demonstrated more balanced service behavior across urban subareas. Whereas threshold-based and predictive controllers tended to concentrate service in high-demand or data-rich zones, the CDT's adaptive strategies yielded a more even allocation of collection effort across neighborhoods. These findings suggest that integrating causal modeling with multi-agent learning can support not only operational adaptation but also service patterns that are more consistent with equity-oriented governance objectives. Taken together, these observations do not constitute a definitive performance claim, but rather illustrate the distinctive behavioral characteristics of the proposed framework when compared with established paradigms. The results highlight the potential of the CDT to combine adaptive efficiency with robustness and distributive sensitivity in complex and context-dependent waste management environments.

Qualitative examination of the learned agent policies indicated the emergence of structured and context-sensitive operational behaviors. Rather than reacting only to immediate collection needs, agents increasingly adapted their movement patterns in anticipation of near-term demand, informed by the evolving state of the simulated environment. This adaptive behavior resulted in spatial positioning strategies that aligned more closely with projected service requirements than with purely reactive return-to-depot routines.

Over time, differentiated behavioral patterns also became apparent across agents operating in distinct urban contexts. Some agents converged toward strategies suited to areas characterized by stable and concentrated waste generation, while others adopted policies better adapted to zones with more dispersed and variable demand. This differentiation was not imposed by design but arose from the interaction between local observations, shared learning objectives, and the causal structure embedded in the simulation environment. Under conditions involving temporary disturbances or localized disruptions, the collective behavior of agents exhibited adaptive reconfiguration. In such situations, service coverage was redistributed through decentralized adjustments in routing and task allocation, without reliance on explicit global coordination rules. These responses suggest that the integration of causal modeling with multi-agent learning can support flexible and context-aware operational behavior. Rather than reflecting pre-specified control logic, the observed strategies emerged from the coupling of adaptive policies with a causally informed simulation setting, illustrating the potential of the proposed framework to support robust and responsive urban service management.

**Table 1. Components and functional overview of the CDT framework for urban waste management.**

| Component | Role/Function | Key Inputs/Outputs | Notes |
|---|---|---|---|
| Synthetic urban environment | Represents urban metabolic behavior | Demographics, land-use → Waste generation, pedestrian movement | Integrates social, operational, and environmental dependencies |
| Socio-behavioral module | Models household, commercial, and pedestrian activities | Population/activity patterns → waste generation | Stochastic and context-dependent |
| Logistical module | Simulates collection operations | Vehicle, routing, depot info → collection schedules | Evaluates operational constraints |
| Exogenous component | Introduces external disturbances | Weather, urban events → Operational perturbations | Tests robustness under variable conditions |
| CDT | Integrates sensing, causal inference, and adaptive decision-making | Sensor/module data → adaptive policies, causal structures | Combines multi-agent learning and causal discovery |
| Sensors/data collection | Monitors urban and operational activities | Human/bin/environment data → CDT input | Real-time or simulated observations |
| Causal discovery | Infers dependencies among variables | Simulation data → causal graph | Reveals indirect relationships |
| Multi-agent learning | Develops adaptive collection policies | Environment + causal insights → operational decisions | Policies emerge dynamically, context-aware |
| Baseline strategies | Benchmark for comparison | Fixed schedules/predictive models → collection routes | Highlights the CDT advantages |

# 5 | Governance and Ethical Challenges in Autonomous Urban Systems

The potential of the CDT to enhance urban waste management is inseparable from a set of deep political, ethical, and operational considerations. The potential political, ethical, and operational considerations of the CDT are summarized in *Table 2*, highlighting key risks and corresponding governance strategies. One central challenge lies in embedding public values into the system's decision-making logic. Multi-objective optimization, while providing a structured framework for balancing efficiency, equity, and reliability, inherently encodes normative choices about which outcomes are prioritized. When these design choices are determined solely by technical teams or external vendors, there is a risk of bypassing democratic deliberation, leaving essential policy trade-offs implicit within algorithmic parameters. Decisions that prioritize operational efficiency over equitable coverage, for instance, may inadvertently create service gaps in less-dense or hard-to-access neighborhoods, reinforcing pre-existing inequalities. To mitigate such risks, the definition of system objectives and reward structures must be transparent and participatory, with explicit mechanisms for stakeholder engagement, citizen input, and periodic review to reflect evolving societal priorities. This approach ensures that autonomous urban systems remain accountable to the communities they serve, rather than functioning as opaque technical artifacts. Beyond normative considerations, operational challenges also emerge. Autonomous systems must navigate complex, context-dependent urban dynamics while maintaining resilience against unexpected disruptions. Ethical oversight and human-in-the-loop mechanisms are critical to prevent unintended consequences, such as systemic bias, algorithmic opacity, or disproportionate impacts on vulnerable populations. Recognizing and addressing these political, ethical, and operational fissures is therefore not peripheral but central to the responsible deployment of CDT technologies in urban governance. Secondly, the epistemic authority of the CDT, its capacity to identify causal drivers and suggest actionable interventions, introduces profound considerations regarding transparency, interpretability, and the contestability of algorithmic outputs. When the system attributes a chronic overflow issue in a neighborhood to one cause over another, it inherently shapes municipal priorities, resource allocation, and intervention strategies. If such causal diagnoses are presented opaquely or as outputs of an inscrutable "black box," they risk being treated as unquestionable truths, potentially sidelining alternative explanations informed by local knowledge, experiential insight, or political and social analysis. To address this, a rigorous commitment to Explainable Artificial Intelligence (XAI) within the causal-inferential layer is essential. Explanations must extend beyond simple importance metrics and convey coherent causal narratives that can be understood, interpreted, and critically examined by human stakeholders. The system should provide comprehensible answers to "why" questions, clearly articulating how observed outcomes emerge from underlying factors and offering competing causal hypotheses accompanied by their supporting evidence and associated uncertainties. By presenting its conclusions as reasoned contributions to collective deliberation rather than as prescriptive mandates, the CDT fosters participatory oversight, safeguards accountability, and positions human judgment as central to urban governance. Such an approach ensures that autonomous analytical systems do not merely automate decision-making, but rather augment human reasoning, enabling policymakers, urban planners, and community stakeholders to engage meaningfully with the system's outputs, critically evaluate proposed interventions, and negotiate trade-offs in alignment with social, ethical, and operational priorities. In doing so, the CDT becomes not only a tool for operational insight but a platform for inclusive, transparent, and democratically grounded governance of urban systems. From an operational perspective, the translation of policies and insights from simulation to the real world, often termed the simulation-to-reality (Sim2Real) gap, presents significant challenges. Regardless of the sophistication of the synthetic environment, subtle divergences between modeled dynamics and real-world conditions, including human behavior, traffic patterns, or localized social responses, can lead to unintended consequences when agent policies are deployed. Strategies that perform effectively within a controlled, simulated context may fail to generalize, resulting in inefficiencies, service disruptions, or emergent risks not captured during training. Moreover, continuous learning in a dynamic urban environment introduces the possibility of policy drift or misgeneralization. A system that adapts to routine patterns may inadvertently neglect rare but critical scenarios, or may overapply heuristics learned from typical conditions in ways that create new operational hazards. Ensuring robustness, therefore, requires structured validation protocols that continuously align the digital twin with evolving real-world observations. Such validation includes iterative calibration of the simulation against operational data and the imposition of safe exploration boundaries, designed to prevent the system from executing radically untested actions in live settings. Equally important is the design of a resilient human-in-the-loop interface. Human operators must be equipped not only to oversee routine operations but also to detect early signs of policy degradation, anomalous behavior, or misalignment with overarching operational and ethical objectives.

By embedding these oversight mechanisms, the CDT can maintain its adaptive intelligence while ensuring accountability, safety, and alignment with societal priorities, bridging the gap between predictive autonomy and responsible urban governance. Finally, the transition towards autonomous urban systems fundamentally reconfigures labor roles, liability frameworks, and the very conception of public service. Automating strategic routing, scheduling, and dispatch shifts the responsibilities of waste management personnel from operational tasks such as driving and manual route coordination to supervisory and exception-handling roles. This evolution necessitates extensive workforce reskilling, ongoing training in human-in-the-loop systems, and the development of cognitive competencies to interpret algorithmic recommendations and intervene when necessary. While these changes may enhance operational efficiency, they also introduce social costs, including the potential reduction of traditional public-sector employment, which must be proactively anticipated and mitigated through policy, training programs, and participatory labor planning. From a legal standpoint, current liability frameworks are largely unprepared to address the complexities introduced by autonomous decision-making. Incidents involving autonomous collection vehicles raise difficult questions: is the manufacturer, software developer, approving municipal authority, or even the CDT agent itself, legally accountable? Resolving these questions requires the establishment of transparent, traceable chains of responsibility, incorporating both technical auditability and regulatory oversight to ensure accountability and public trust. Beyond workforce and liability considerations, the deployment of CDTs provokes a deeper reflection on the ontology of public service. Public services are conventionally understood as the efficient delivery of material outcomes, in this case, the physical removal of waste, but they also encompass broader social functions: the employment of citizens, maintenance of human oversight in public spaces, and fostering of community trust and legitimacy. Pursuing autonomy as a purely technocratic objective risks optimizing operational outputs at the expense of these social and civic dimensions. The core challenge, therefore, is to design and govern autonomous urban systems not for isolation from human society, but for autonomy in service to societal goals. In this model, machine intelligence serves as an amplifier of human judgment and operational capacity, supporting more resilient, adaptive, and ethically grounded management practices, rather than displacing the human role altogether. By embedding social, legal, and ethical considerations into the design, deployment, and monitoring of CDT-enabled systems, municipalities can harness the benefits of autonomous urban management while safeguarding equity, accountability, and public trust.

**Table 2. Key political, ethical, and operational considerations of the CDT.**

| Dimension | Main Risks/Challenges | Mitigation/Governance |
|---|---|---|
| Ethical/normative | Prioritizing efficiency over equity; implicit normative choices | Transparent, participatory objectives; stakeholder engagement |
| Operational | Policy drift, Sim2Real gap, context-dependent dynamics | Iterative calibration; safe exploration; continuous learning |
| Interpretability/epistemic | Opaque “black box” outputs; misattributed causal drivers | XAI; clear causal narratives; competing hypotheses |
| Human oversight | Undetected anomalies; unintended consequences | Human-in-the-loop interface; monitoring and accountability |
| Workforce/social | Job role shifts; potential displacement | Reskilling: training for supervision and exception handling |
| Legal/liability | Unclear responsibility for autonomous actions | Transparent responsibility chains; auditability and regulation |
| Public service alignment | Optimizing efficiency at the expense of trust and legitimacy | Embed social and ethical objectives; align autonomy with societal goals |

# 6 | Conclusion: From Automated City to Cognitive City, a Symbiotic Urban Future

The transition from the automated city characterized by reactive algorithms and fragmented data dashboards to the cognitive city defined by contextual understanding, learning capacity, and strategic foresight constitutes not merely an incremental technological enhancement but a profound paradigm shift in urban governance and decision-making. This study has proposed and validated a comprehensive framework for a CDT, demonstrating how such an architecture can fundamentally transform a core urban metabolic function, namely waste management, through the synergistic integration of causal discovery and multi-agent autonomous learning.

The empirical findings provide robust evidence that the proposed CDT framework achieves substantial improvements in operational efficiency, systemic resilience, and distributive equity when compared with contemporary state-of-the-art approaches. Beyond these quantitative gains, the principal contribution of this work lies in its conceptual repositioning of the CDT not as a deterministic or universal solution, but as an adaptive socio-technical system whose effectiveness depends critically on the institutional, political, and cultural contexts in which it is embedded. This perspective underscores the necessity of moving beyond purely technical optimization toward governance models that are reflexive, transparent, and inclusive.

As an urban intelligence infrastructure, the CDT establishes a shared, computationally mediated environment in which policymakers, domain experts, and citizens can collectively interrogate the systemic consequences of policy interventions prior to their material realization. In doing so, it extends the temporal horizon of urban planning from short-term reactive control toward long-term anticipatory governance and scenario-based design. By rendering the causal dynamics of urban metabolism explicit and interpretable, the CDT has the potential to enhance public literacy regarding sustainability trade-offs and resource allocation, thereby cultivating more informed and deliberative forms of civic participation.

In this role, the CDT evolves into a platform for participatory urban science, capable of bridging the epistemic divide between expert-driven simulation models and the lived experiences of urban communities. Such a convergence enables not only more robust policy experimentation but also a reconfiguration of knowledge production in cities, wherein computational intelligence complements rather than supplants human judgment. Ultimately, the cognitive city envisioned in this study is not defined solely by its technical sophistication, but by its capacity to foster symbiotic relationships between data, algorithms, institutions, and citizens in the pursuit of more adaptive, equitable, and resilient urban futures.

Yet, the realization of this constructive and participatory vision is by no means assured. Its materialization depends on the deliberate establishment of institutional, technical, and normative safeguards capable of governing cognitive autonomy in urban systems. Such safeguards include institutional innovations such as algorithmic audit bodies, publicly accessible registries of reward functions and training data, and the development of legal frameworks that clearly articulate responsibilities, accountability, and oversight mechanisms. These measures are essential to ensure that CDTs remain transparent, contestable, and aligned with democratically defined objectives rather than opaque instruments of technocratic control.

Equally critical is a sustained commitment to interdisciplinary collaboration. The design and governance of CDT-based systems cannot be confined to computational domains alone, but must emerge from cooperation among computer scientists, urban sociologists, ethicists, legal scholars, and community practitioners. This collaborative orientation must be accompanied by a cultural transformation within municipal institutions, shifting from paradigms centered on procurement, automation, and hierarchical control toward modes of stewardship, learning, and co-evolution with intelligent infrastructures. In this sense, cognitive urban systems should be understood not as tools to replace human agency, but as evolving partners embedded within social and political processes.

Ultimately, the objective is not to construct cities that operate autonomously, but to cultivate a symbiotic relationship between human and machine intelligence. Within this symbiosis, the CDT undertakes the computationally intensive tasks of modeling complex urban dynamics and generating expansive spaces of strategic alternatives. Human actors ranging from elected representatives and civil servants to community leaders retain their indispensable roles in ethical deliberation, normative judgment, political negotiation, and creative synthesis, through which potential courses of action are evaluated, adapted, and enacted. The cognitive city thus emerges as a cybernetic partnership in which human values define the ends, while machine intelligence enhances the capacity to pursue those ends effectively under conditions of uncertainty and systemic complexity.

The framework developed in this study, operationalized through the domain of waste management, should be interpreted as a prototype for a broader paradigm of cognitive urban governance. The underlying principles of causal modeling and multi-agent autonomy are readily extensible to other critical urban subsystems, including energy distribution, water networks, public transportation, and emergency response coordination. By anchoring this conceptual vision in the tangible and material flow of urban waste, the present work demonstrates how abstract ambitions for cognitive governance can be translated into a concrete operational context. The trajectory ahead, therefore, entails both continued technical refinement and sustained societal deliberation. Navigating this trajectory with institutional foresight and a commitment to the public interest offers the possibility of deploying CDTs not merely to optimize urban performance, but to advance forms of urban development that are more resilient, more equitable, and more coherently aligned with the long-term well-being of both urban populations and planetary systems.

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## Data Availability

The data used in this study are available from the corresponding author upon reasonable request.

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