



SCHEMA FOR AI DRIVEN MUNICIPALITY

WHY A SIMPLE CHATBOT IS NOT ENOUGH

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ABSTRACT

Many municipalities adopt artificial intelligence without knowing if their supporting data is accurate, turning municipal decision-making into an opaque "black box." To address this, we introduce the AI Flow for Municipalities, an evidence-led orchestration system developed under the Czech CESMOD project. Built upon the national Smart Cities Concept, the system utilizes the 4-Diamonds framework and an expert-curated Information and Data Platform (IDP) to map unstructured municipal queries into multi-sectoral, policy-compliant recommendations. By providing auditable data provenance and clear contextual logic, this transparent framework enables genuinely data-driven territorial development and offers a scalable model for explainable AI governance.

1. Introduction

In an era of rapid urban transformation, modern municipalities increasingly turn to digital innovations and artificial intelligence (AI) to address complex, multi-sectoral challenges ranging from public infrastructure management to sustainable local governance (Zhu, 2026). Local public administrations frequently deploy conversational interfaces, automated tools, and generative language models to improve operational efficiency, reduce administrative burdens, and enhance communication with citizens (Senadheera et al., 2025). However, integrating these systems into daily municipal workflows requires navigating complex technical, organizational, and normative challenges (Neumann et al., 2024). Many local governments may adopt AI solutions as isolated "black boxes" without knowing whether they possess the appropriate, accurate, and contextually relevant data needed to support sound decision-making (Roehl & Hansen, 2024). Because traditional large language models operate on word correlations rather than real-world comprehension of legal, spatial, or socio-demographic contexts, administrators are often left unaware of how specific system outputs are generated, triggering ethical, legal, and operational risks. For example, automated systems trained on historical data risk institutionalizing and compounding past societal biases under the guise of mathematical neutrality, effectively "predicting the past" rather than enabling progressive policy (Pesch, 2025).

To overcome the failure of isolated, single-context tools and opaque automated reasoning, public administration requires context-aware decision support grounded in standardized policy frameworks and auditable evidence bases. In the Czech Republic, a strategic foundation for urban transformation has been established at the national level through the Smart Cities Concept: Resilience through SMART Solutions for Municipalities, Cities, and Regions up to 2030 (Ministry of Regional Development of the Czech Republic, 2021) and its accompanying Implementation Plan (Ministry of Regional Development of the Czech Republic, 2024). This governmental strategy recognizes that urban issues cannot be resolved through fragmented digital interventions; rather, they demand a holistic, multi-contextual approach grounded in the Seven Core SMART Principles and structured into 16 functional components. Nevertheless, like any high-level governmental document, the Smart Cities Concept can only achieve its intended impact if it is operationalized through practical, evidence-based tools that local leaders, innovation brokers, and public managers can actively use in daily administrative workflows.

This article presents a practical pilot solution currently being developed within the Czech Republic's research ecosystem under the CESMOD project. Designed to bridge the gap between national strategic visions and local execution, this pilot tool, termed *the AI Flow for Municipalities*, utilizes a context-aware multi-agent orchestration architecture. By leveraging the 4-Diamonds modeling logic (specifically the Recognize Diamond) and connecting to an integrated Information and Data Platform (IDP), the system transforms unstructured municipal queries into multi-sectoral, evidence-grounded recommendations. Through basic testing on real municipal contexts, this paper demonstrates how a structured AI pipeline can eliminate algorithmic opacity, respect local governance constraints, and actively translate national SMART principles into auditable, synergistic urban decision-making.

2. Multicontextuality and its role

In this chapter, we discuss multicontextuality as one of the core parameters of Smart City and AI-driven municipal development. The aim is to show that municipal innovation can't be reduced to isolated digital tools or simple technical interventions. Instead, Smart City projects should be understood as service ecosystems where actors, data, infrastructures, goals, and value propositions interact across several contexts at once (Walletzky et al., 2020).

2.1. Multicontextuality as a defining feature of Smart City projects

Multicontextuality can be understood from two complementary perspectives. The first perspective is structural. It follows the layered view of Smart City services, where services are organized into interdependent layers. Some services are directly visible to citizens as customer-facing services, while others remain in the background as supporting or infrastructure services. Although these background services are not perceived by the final user, they are essential for the quality, reliability and value of the visible service (Walletzky et al., 2018).

The second perspective is context-driven. Here, the key point is that one service, actor, dataset or infrastructure element can appear in two or more contexts, while its role and meaning may differ in each of them. For example, one service can be part of mobility, energy, safety or environmental contexts at the same time. To understand the real effect of a change or a newly designed service, it is therefore necessary to map all contexts in which the service appears and analyze how its role changes across them (Walletzky et al., 2023a).

Together, these two perspectives show why Smart City projects can't be designed as isolated solutions. The layered perspective reveals dependencies between visible and invisible services, while the context-driven perspective reveals how the same service can influence several domains at once. Multicontextuality therefore becomes a practical requirement for service design, municipal innovation and AI-driven decision support.

2.2. Why simple and isolated solutions fail

Simple solutions often fail because they ignore both perspectives of multicontextuality. From the layered perspective, they usually focus only on the visible, customer-facing part of the service and overlook the supporting and infrastructure services that determine whether the solution will actually work. A digital service can look simple to the citizen, but its quality depends on data flows, software, hardware, organizational routines and maintenance.

From the context-driven perspective, simple solutions fail because they are designed for only one dominant context. A service created as a "mobility solution" can also affect energy demand, air quality, emergency response, public space or citizen participation. If these additional contexts aren't mapped, the solution can produce unintended costs, conflicts or lower value in other parts of the municipal system.

This is why Smart City development shouldn't start with the question "Which technology should we implement?" but rather "Which contexts and service layers will be affected?" A multicontextual approach doesn't make the solution more complicated for the user; it makes the design process more responsible, because it reveals dependencies before implementation. (Buhnova et al., 2022; L. Walletzky et al., 2019; Walletzky et al., 2023b)

2.3. Multicontextuality as a basis for innovation and resilience

Multicontextuality is not only an analytical challenge; it is also a source of innovation. The layered perspective helps municipalities identify how existing background services, data sources and infrastructures can support new customer-facing services. Innovation often emerges when already existing resources are recombined into new value propositions instead of building isolated tools from scratch.

The context-driven perspective strengthens this potential by showing that one service can create value in several contexts at once. A well-designed service can support mobility, sustainability, safety and participation simultaneously, if its roles in these contexts are understood. This is also the basis of the SMART principle of "one solution with multiple effects".

Multicontextuality also supports resilience. A resilient municipal service must react to changes without collapsing the surrounding ecosystem. This requires knowledge of service dependencies, affected actors and contextual overlaps. Resilience is therefore not a separate feature added after design; it must be embedded into the service model from the beginning. (Dragoicea & Walletzky, 2020; Lusch & Nambisan, 2015; Schwarzová et al., 2024a)

2.4. The Necessity of Context-Awareness in Municipal AI

For AI-driven municipalities, both perspectives of multicontextuality are essential. From the layered perspective, AI can't operate only at the visible interface, such as a chatbot or citizen portal. Its usefulness depends on the quality of supporting services: available data, semantic structure, interoperability, process rules, infrastructure and institutional responsibilities.

From the context-driven perspective, AI must be able to recognize that the same input can have different meanings in different municipal contexts. A citizen request, a dataset or a municipal measure can relate to several domains at once. If AI works only with one context, it may generate technically correct but practically misleading recommendations. The academic research on public sector AI adoption suggests that AI cannot be useful, lawful, or ethically sustainable in local governments unless it considers and understands the context in which its decisions are made (Roehl & Hansen, 2024). Administrative decisions in local authorities are never abstract; they are deeply contextual, shaped by the complexity of the case, the ambiguity of local regulations, and formal and informal civil service norms (Goldsmith & Yang, 2026).

Individuals and organizations operate in highly complex, uncertain environments (Wang et al., 2024). In such environments, the value of AI lies not in replacing human judgment, but in strengthening the capacity of local public bodies to dynamically identify emerging societal needs, expect policy failures, and tailor administrative services in ways that are contextually meaningful and aligned with public values (Zhu, 2026).

Ultimately, local governance is a cooperative, socio-technical endeavor built upon active interactions between citizens, street-level bureaucrats, and institutional frameworks. To cultivate the ability of civil servants to exercise judgment flexibly while maintaining ethical control, AI orchestration in local governments must transition away from context-blind conversational portals (Goldsmith & Yang, 2026). Instead, modern municipalities require context-aware, multi-agent frameworks. Such architectures must be capable of dynamically segmenting and analyzing unstructured municipal queries — incorporating user roles, socio-demographic indicators, and spatial variables — and routing them to specialized, domain-specific AI agents. (Roehl & Hansen, 2024). This means that an AI-driven municipality needs more than a conversational interface. It needs a multicontextual service architecture that connects data, goals, actors, rules and value propositions. Only then can AI support municipal development as an orchestration tool rather than as another isolated digital solution (Maglio et al., 2009; Schwarzová et al., 2024b)

3. Smart City methodology in Czechia

To systematically transform urban and rural environments, the Czech Republic established a centralized, standardized framework through the national Smart Cities Concept: Resilience through SMART Solutions for Municipalities, Cities, and Regions up to 2030 (hereinafter referred to as the Concept), managed by the Ministry for Regional Development. The methodology explicitly recognizes that municipalities are non-homogenous entities operating under a dense, highly fragmented settlement structure (comprising over 6,250 municipalities). Rather than treating smart urban development as a disjointed procurement of fragmented digital tools, the Czech methodology introduces an overarching, systemic strategy designed to enhance local self-sufficiency, social cohesion, and climate adaptability. (Ministry of Regional Development of the Czech Republic, 2021)

However, when evaluated against current municipal practices, a critical gap emerges: local governments frequently misinterpret "smart governance" as the mere deployment of isolated, conversational interfaces such as basic customer-service chatbots. While a simple chatbot provides a superficial communication interface for answering basic citizen queries, it fundamentally fails to interoperate with multi-sectoral datasets or act upon the complex operational workflows required by municipal authorities. To prove why such narrow tools are inadequate and to construct an advanced, multi-contextual AI governance schema (e.g., the

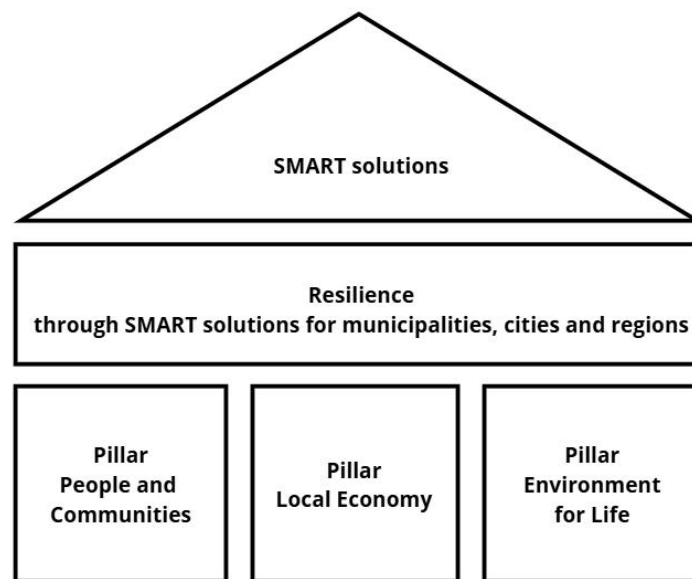
CESMOD architecture), it is first necessary to examine the structural foundation, governing principles, and implementation mechanisms of the Czech Smart City methodology. (Ministry of Regional Development of the Czech Republic, 2021)

3.1. SMART concept

The Czech SMART concept is conceptualized as an integrated "house" model designed to achieve long-term resilience, carbon neutrality by 2050, and digital transformation. The structural framework is anchored by three foundational pillars representing sustainable territorial development, overlaid by a horizontal cross-cutting domain like in **Figure 1**. These part are more described as follows:

- Overarching Cross-Cutting Domain – Resilience through SMART Solutions emphases on digital public administration, transparent governance, horizontal/vertical inter-municipal coordination, cyber security, and international cooperation. Contains 4 components, labelled ZPO1 – ZPO4.
- Pillar A: People and Communities (Resilient Regions): Addresses inclusive education, accessible health and social care integration, social cohesion, anti-fragmentation housing strategies, and rapid crisis response. Components here are labelled A1 – A4.
- Pillar B: Local Economy (Competitive Regions): Focuses on local entrepreneurship, decentralized renewable energy generation, smart grids, circular economy and robust ICT infrastructure deployment. Components here are labelled B1 – B4.
- Pillar C: Living Environment (Green Regions): Emphasizes air quality management, blue and green infrastructure, climate adaptation, precision agriculture, and sustainable multimodal mobility. Components here are labelled C1 – C4.

Figure 1. Schema of SMART City Concept or Structure of the Smart Cities Concept



Source: Translated from (Ministry of Regional Development of the Czech Republic, 2021)

The 16 functional components embedded within these pillars and overarching cross-cutting domain establish that urban governance is inherently multi-contextual. A single municipal event (e.g., torrential flooding) simultaneously triggers workflows across component A4 (Integrated Rapid Response), C3 (Blue-Green Infrastructure drainage), B4 (ICT sensor networks), and ZPO1 (Digital Public Administration). A basic, single-context chatbot is architectural incapable of processing or orchestrating such cross-domain dependencies. (Ministry of Regional Development of the Czech Republic, 2021)

3.2. Seven SMART Principles

To guide municipal decision-making and prevent vendor lock-in or disjointed technology deployments, the Czech methodology mandates that every smart intervention must comply with Seven Core SMART Principles (Ministry of Regional Development of the Czech Republic, 2021):

To evaluate whether an urban intervention or digital tool qualifies as a "SMART solution," the national methodology establishes seven mandatory governing SMART principles. These principles serve as evaluation criteria for municipal projects and provide the logical requirements for autonomous urban AI reasoning. (Ministry of Regional Development of the Czech Republic, 2021)

- **Principle of Direction Change:** Establishing conditions that enable citizens, businesses, and public servants to access services and perform work remotely or within close proximity to their homes, reducing physical commuting demands.
- **Principle of Resilience:** Enhancing the capacity of communities, local economies, and ecosystems to absorb disruptions, adapt to environmental/socio-economic crises, and maintain continuous operational functionality through digital innovations.
- **Principle of Single Solution with Multiple Effects:** Mandating a holistic, multi-sectoral design where a single technological or organizational intervention simultaneously addresses multiple urban needs.
- **Principle of Short Distances:** Ensuring that all essential services, resource flows, and governance interactions are handled locally or within the shortest geographical/procedural distance, adhering to the 3E rule (Economy, Efficiency, Effectiveness).
- **Principle of Collaboration and Financial Sustainability:** Promoting multi-stakeholder participation across the Quadruple Helix innovation model (public sector, academia, industry, citizens) and guaranteeing full life-cycle cost sustainability through multi-source funding.
- **Principle of Cohesion, Complementarity, Horizontal and Vertical Integration:** Eliminating regional disparities, bridging the digital divide, and ensuring seamless interoperability between municipal, regional, and central state administrative levels.
- **Principle of Evidence-Based Solutions:** Driving municipal planning through systematic data collection, open data standards, spatial modeling, and transparent information sharing (Ministry of Regional Development of the Czech Republic, 2021)

Furthermore, these seven SMART principles are automatically integrated into the system prompts of all AI agents operating within the SMART framework to ensure consistent alignment with national governance standards. (Ministry of Regional Development of the Czech Republic, 2021).

4. CESMOD project and the basic architecture

The preceding sections establish the importance of interpreting municipal problems across policy domains and relating proposed interventions to local conditions. CESMOD provides the research and application setting for developing this approach through the AI Flow for Municipalities. Its contribution to the proposed methodology lies in connecting research on municipal needs with structured knowledge resources and support for their practical use. This section explains these relationships and their implications for the design of municipal decision support.

4.1.From the SMART Concept to Municipal Needs

The Czech SMART Concept provides a common policy framework comprising 16 functional components and seven guiding principles. Applying this framework requires municipal actors to relate broad development objectives to specific local problems, identify relevant interdependencies and assess the suitability of possible interventions. The practical challenge is therefore to translate the framework into options that reflect the priorities and capacities of individual municipalities.

CESMOD addresses this challenge through research on territorial innovation and SMART development. Its human-centred orientation places technological opportunities within the organisational and social conditions in which innovations are introduced. Differences in staffing, access to expertise, institutional capacity and public acceptance can influence whether a proposed measure is feasible and appropriate. These conditions are relevant to decision support because recommendations require interpretation in relation to the municipality's resources and development priorities.

Within this setting, the AI Flow is intended to help municipal representatives and innovation brokers examine development options using the SMART framework and relevant supporting information. Its role is to make relationships between a municipal request, affected policy domains and potential measures explicit. Municipal actors retain responsibility for assessing feasibility, resolving competing priorities and deciding whether and how to proceed. The value of the proposed support consequently depends on both the information it provides and the ability of users to critically assess that information.

4.2.Knowledge Infrastructure and Innovation Brokerage

The Information and Data Platform (IDP) provides the knowledge infrastructure for the proposed methodology, encompassing local indicators, SMART component descriptions, and good-practice examples. The AI Flow leverages these resources to align municipal requests with local conditions and transferable experiences. Effective decision support relies heavily on source quality, currency, and contextual relevance.

While the current prototype retrieves a limited set of structured resources via a local data connector (described in Section 6), it must be distinguished from the broader database planned within the wider CESMOD program. The latter develops theoretical and methodological foundations for smart cities, regions, and communities by combining qualitative and quantitative research with strategic document analysis. Natural language processing, machine learning, and statistical analysis support this research to examine local needs, implementation barriers, and policy priorities. Although these activities inform the continuous expansion of the knowledge base, their full integration into the AI Flow lies beyond the current prototype.

Organizational connections between these knowledge resources and municipal practice are established through innovation brokerage. Within CESMOD, SMARTNET.cz supports a network of innovation brokers who help identify municipal needs and connect them with relevant tools and expertise. Within the AI Flow, brokers assist in formulating requests, interpreting recommendations, and identifying missing evidence, providing a structured setting for human review. Complementing this support, the planned SMART Academy focuses on education and capacity building to strengthen understanding of the SMART Concept.

Together, these relationships highlight three core design requirements for the proposed decision-support approach: sensitivity to municipal context, explicit links between recommendations and supporting evidence, and outputs that municipal representatives and

innovation brokers can critically assess. The SMART components and principles provide the governing policy framework to address these requirements.

5. Methodology of the AI Flow for Municipalities

To address the inherent complexity of municipal decision-making and overcome the limitations of isolated, single-context conversational agents (chatbots), this section introduces a context-aware AI orchestration methodology. Developed within the framework of the CESMOD project, this methodology is designed to translate unstructured municipal requests into multi-sectoral, evidence-based, and policy-compliant decision support. The core of this methodology lies in recognizing that local governance challenges are multi-contextual “wicked problems” where a single urban intervention simultaneously triggers workflows and impacts across multiple domains.

5.1. The Challenge of Identifying Dominant Contexts

In municipal administration, the primary decision-making problem is not merely processing a request, but identifying and determining the dominant contexts that are relevant to assessing a given problem. When a local representative (e.g., a mayor, innovation broker, or department head) poses a query or identifies an issue, that issue does not exist in a vacuum. Any proposed action creates a ripple effect across different municipal domains, generating both positive and negative side-effects, trade-offs, and synergies.

For example, a municipal proposal to implement energy-saving measures in public buildings is commonly categorized as a simple environmental or technical task. However, a holistic assessment reveals that this intervention simultaneously affects environmental, economic/financial, and social/community contexts.

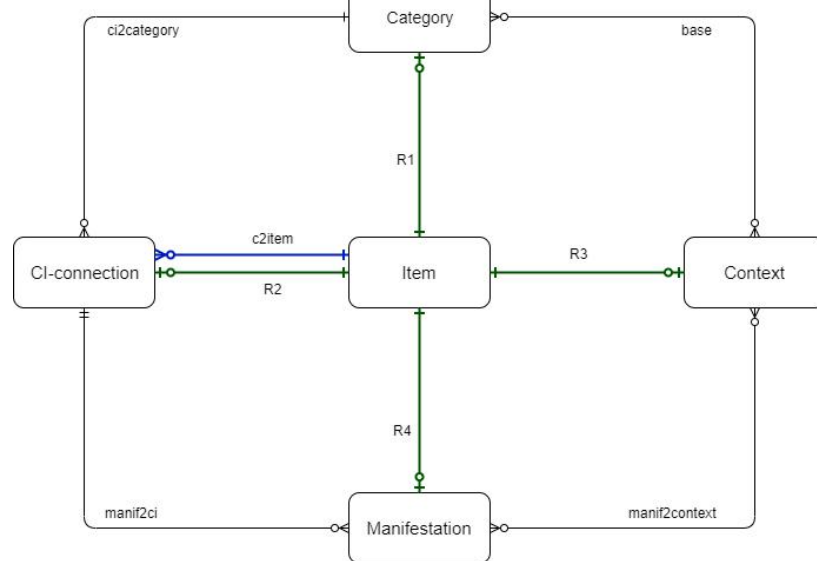
- **The Environmental Context:** Direct reduction of carbon emissions and energy consumption.
- **The Economic/Financial Context:** Capital expenditure, long-term operational savings and available subsidy programs.
- **The Social/Community Context:** The comfort, health, and social cohesion of the citizens using those buildings.

If the decision-making process is blind to these overlapping domains, the municipality risks implementing “simple solutions” that fail because they ignore background dependencies or create unintended negative externalities in other sectors. Thus, the fundamental challenge of a municipal AI orchestration system is context recognition—specifically, identifying dominant contexts that must be activated to evaluate the holistic effects, principles, and values created by any proposed intervention.

5.2. Conceptual solution - Recognize Diamond

The Recognize Diamond is a part of 4-Diamond model, developed by (Stanicek, 2009) and adopted for SMART service usage by (Dragoiea & Walletzký, 2020). It provides a conceptual framework for explaining how a municipal issue can be interpreted across multiple domains. Its purpose is not only to classify a request into one administrative category, but to identify how the same subject of interest may acquire different meanings in different contexts. This is essential for municipal AI orchestration because a single input, such as a request regarding public buildings, energy savings, composting, or optical infrastructure, may simultaneously involve technical, environmental, financial, social, and governance dimensions.

As illustrated in the conceptual model (Figure 2), the Recognize Diamond consists of five core entities and their relationships: Item, Context, Category, Category-Item Connection, and Manifestation. The Item is the central entity representing the subject of interest or the underlying phenomenon. It can be a physical object, an infrastructure element, a service, a process, or a municipal problem—for example, a car, a public building, a composting facility, or an optical network.

Figure 2. Diagram of Diamond Recognize

Source(s): Badr et al., 2021

The Context represents the specific domain, application field, or perspective in which the Item is examined. In the proposed methodology, contexts are operationalized through the 16 functional components of the national SMART Concept, ranging from A1–A4, B1–B4, C1–C4, and ZP01–ZP04. This means that context recognition is not an arbitrary semantic exercise: each identified context must correspond to one of the components of the SMART framework.

The relationship between the Item and the Category is expressed through a Category-Item Connection. This connection can be understood as a vector represented by the triplet (*Item, Category, Probability*). It indicates how strongly or how probably a given Item belongs to a specific Category within a given Context. In an AI orchestration workflow, this allows the system to avoid purely binary classification. Instead of deciding that a query belongs to only one component, the system can estimate which contexts are dominant and which are only secondary or irrelevant.

The final entity is Manifestation. A Manifestation is the concrete, observable representation, data point, behaviour, or evidence through which the Item becomes visible in a particular Context and Category. For example, if a car is interpreted as a source of pollution, its manifestations may include measured emissions, noise levels, or traffic counts. If the same car is interpreted as a data source, its manifestations may include telemetry records or sensor data. In municipal decision-making, manifestations connect abstract context recognition with evidence: local indicators, datasets, good practices, funding schemes, and policy documents.

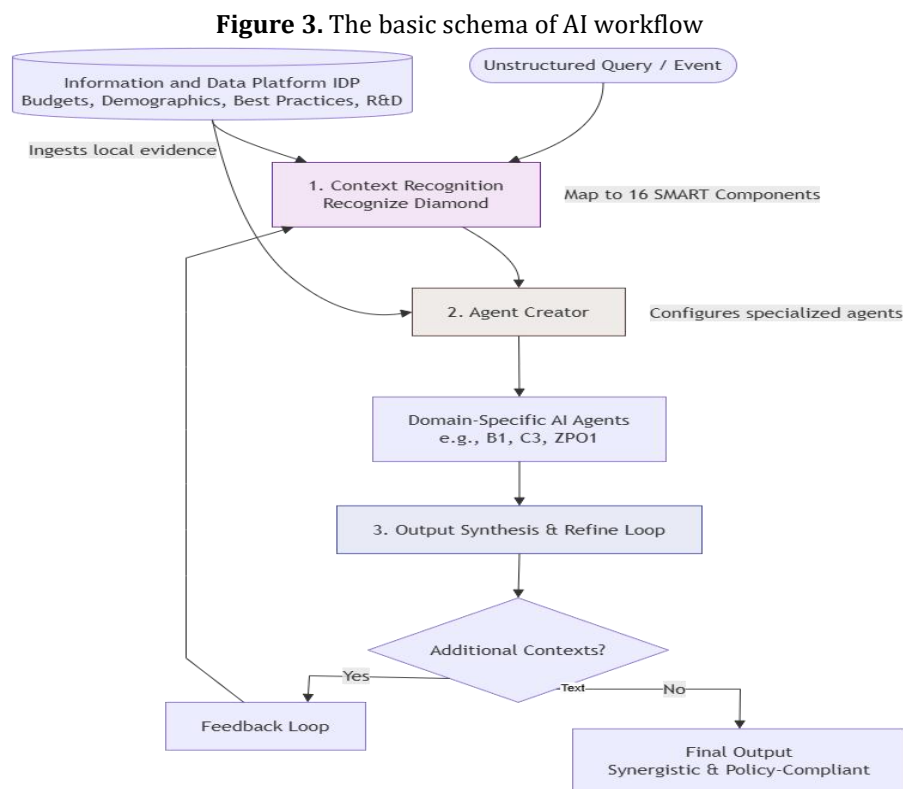
In our solution, this conceptual structure is simplified into an executable routing logic. The Item is extracted from the user query, relevant manifestations and contextual variables are considered, and the system estimates which SMART components should be activated. The Recognize Diamond therefore serves as the conceptual bridge between an unstructured municipal request and the component-based orchestration process described in the following section.

Crucially, the system does not learn or map these manifestations through superficial keyword matching or unverified web-scraping. Instead, the creation and learning of the manifestation database rely on curated Good Practice Examples collected and structured by component experts within the CESMOD project. During the ingestion phase into the Information and Data Platform (IDP), experts manually annotate each good practice example, explicitly linking its description and operational attributes to the relevant national SMART components. This expert-curated repository serves as the ground-truth baseline for the Recognize Diamond. When a new unstructured municipal request is processed, the AI engine evaluates whether the extracted

Item and its observed manifestations can be semantically categorized under the existing manifestation patterns stored in the database. Rather than a binary classification, this process establishes a Category-Item Connection probability vector $v = (Item, Category, P)$, where $P \in [0, 1]$. If the new input exhibits high semantic alignment with the established expert-verified manifestations of a specific component, the probability P approaches 1. Conversely, if discrepancies or weak contextual links are detected, P drops toward 0. Consequently, the performance and accuracy of this context-recognition mechanism depend directly on the availability, volume, and domain quality of the expert-validated good-practice database maintained within the CESMOD ecosystem.

5.3. The Orchestration Workflow: The AI Flow for Municipalities

To operationalize the Recognize Diamond within a digital governance framework, we translate this conceptual logic into a three-stage orchestration workflow, termed the AI Flow for Municipalities (Figure 3). The workflow describes how an unstructured municipal request is first interpreted as a context-rich issue, then routed to the relevant SMART components, and finally transformed into an evidence-based recommendation through synthesis and refinement. At this methodological level, the workflow coordinates natural language understanding, municipal data resources, component-specific reasoning, and feedback-based refinement into one coherent decision-support process.



Source(s): Authors'elaboration, 2026

Stage 1: Input and Context Recognition (Recognize Diamond)

The workflow begins when a municipal actor inputs an unstructured, natural language request, such as: "I want to solve energy savings for buildings in our municipality". The system immediately applies the Recognize Diamond to extract the core Item, evaluate its Manifestations, define role-based and spatial boundaries, and get the context-specific data from Information and Data Platform (IDP), including statistical indicators, basic data about the municipality, and its specifics to get initial context.

Stage 2: Component Routing and Agent Configuration

Once the initial context is structured and bounded, the system maps the query to the national SMART Concept framework and identifies which of the 16 core functional components are primary touchpoints. This process is also based on the Recognize diamond, but here the system explores the evidence of specific manifestations to identify the context, that is, here represented by one of 16 components. In the energy example, the system may flag C3 (Green and Blue Infrastructure), B1 (Local Economy), and ZPO2 (Resilience/Cohesion) as dominant contexts. At the conceptual level, this stage includes both routing to relevant components and configuring component-specific AI agents. The selected components are linked to structured data from the IDP, including good practices, subsidy programs, relevant strategies and target indicators.

Stage 3: Evidence-Based Synthesis and Refinement

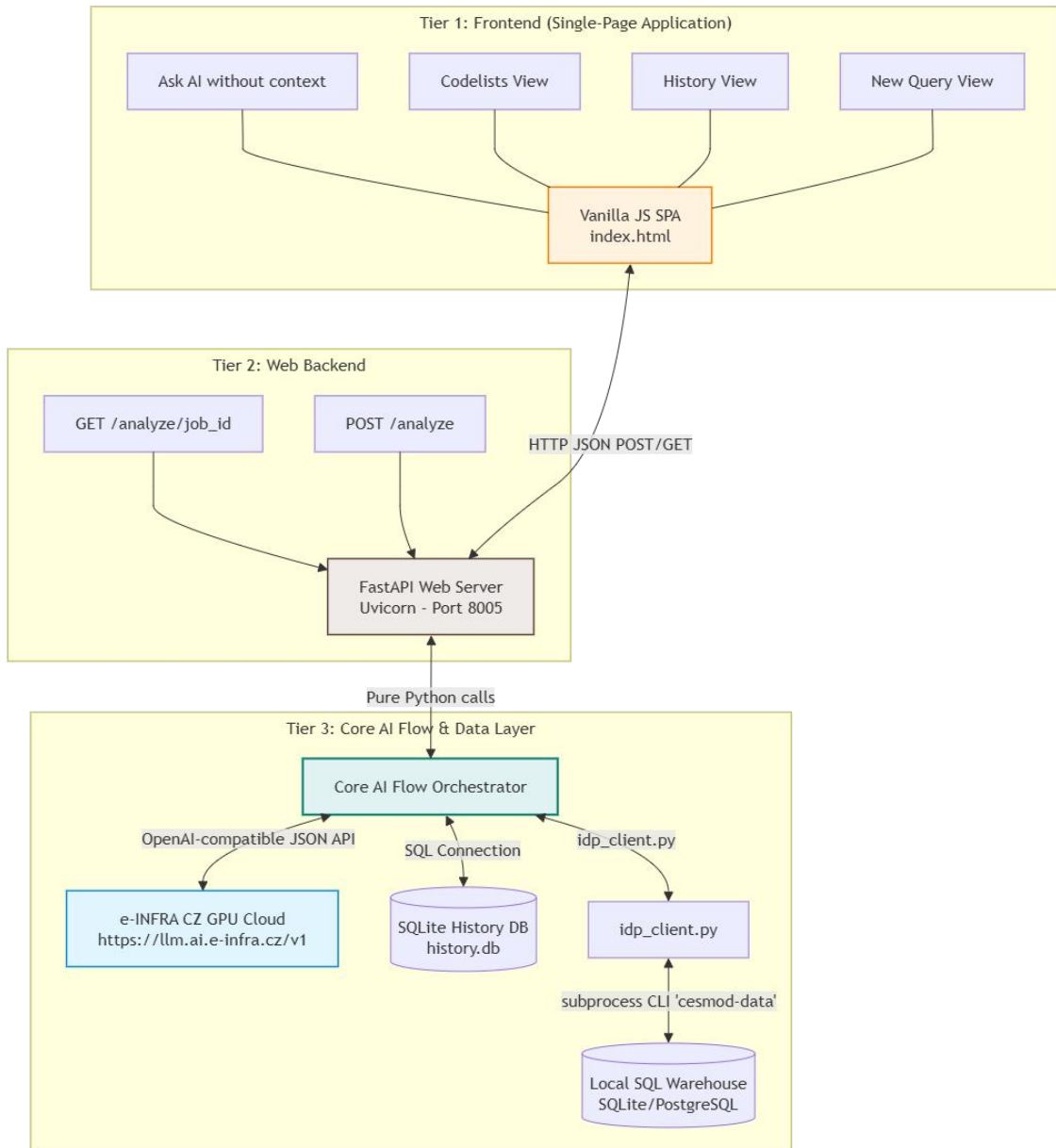
The outputs and recommendations from the component-specific agents are aggregated into a unified primary proposal. At the conceptual level, this stage covers both evidence-based synthesis and the secondary feedback mechanism. The system analyzes potential synergies, conflicts, and trade-offs against the 7 Core SMART Principles. If additional contexts or conflicts are detected, the query is enriched and returned to context recognition for refinement; if not, the system compiles a final, policy-compliant output containing tailored recommendations, eligible funding streams, and relevant best practices.

6. Proof of Concept and Application Implementation

This chapter reports the current Proof-of-Concept implementation of the Minimum Viable Product introduced in Section 5.4. The PoC/MVP prototype demonstrates how a structured, context-aware digital framework can transform unstructured administrative requests into policy-compliant, evidence-led local development plans.

6.1. Software Architecture

The PoC/MVP prototype is constructed using a lightweight, secure, and localized three-tier architecture designed to support rapid deployment, containerization, data sovereignty, and alignment with public-sector security requirements. The architecture (Figure 4) consists of a Vanilla JavaScript single-page frontend, a FastAPI web backend, and a modular Python Core AI Flow connected to a localized data connector and a SQLite history database.

Figure 4. Software architecture of the prototype

Source(s): Authors'elaboration, 2026

6.2. Frontend and Backend Tier

The user interface is implemented as a single-page application encapsulated in a single file using Vanilla JavaScript. This design avoids the dependency overhead of modern JavaScript frameworks and supports predictable loading and rendering in standard municipal browsers. The frontend exposes three primary views: New Query, History, and Codelists. The New Query view supports unstructured municipal requests and contextual variables; the History view enables retrieval and display of stored analyses; and the Codelists view presents registered roles, strategic purposes, and spatial environments used to bound the context. A benchmark module, Ask AI without context, is embedded directly within the New Query view for immediate comparison with unstructured LLM output.

The web server is implemented using FastAPI running on the Uvicorn ASGI server. Rather than maintaining long-lived WebSocket connections, the backend manages long-running analysis workflows asynchronously through a thread pool. Communication with the frontend

relies on a polling model over two REST endpoints: POST /analyze, which ingests the query and returns a job identifier, and GET /analyze/{job_id}, which enables the client to poll progress and retrieve the structured JSON output. Additional endpoints provide history retrieval, metadata disclosure, and diagnostic environment validation.

6.3.e-INFRA CZ Academic Research Infrastructure and Core AI Flow

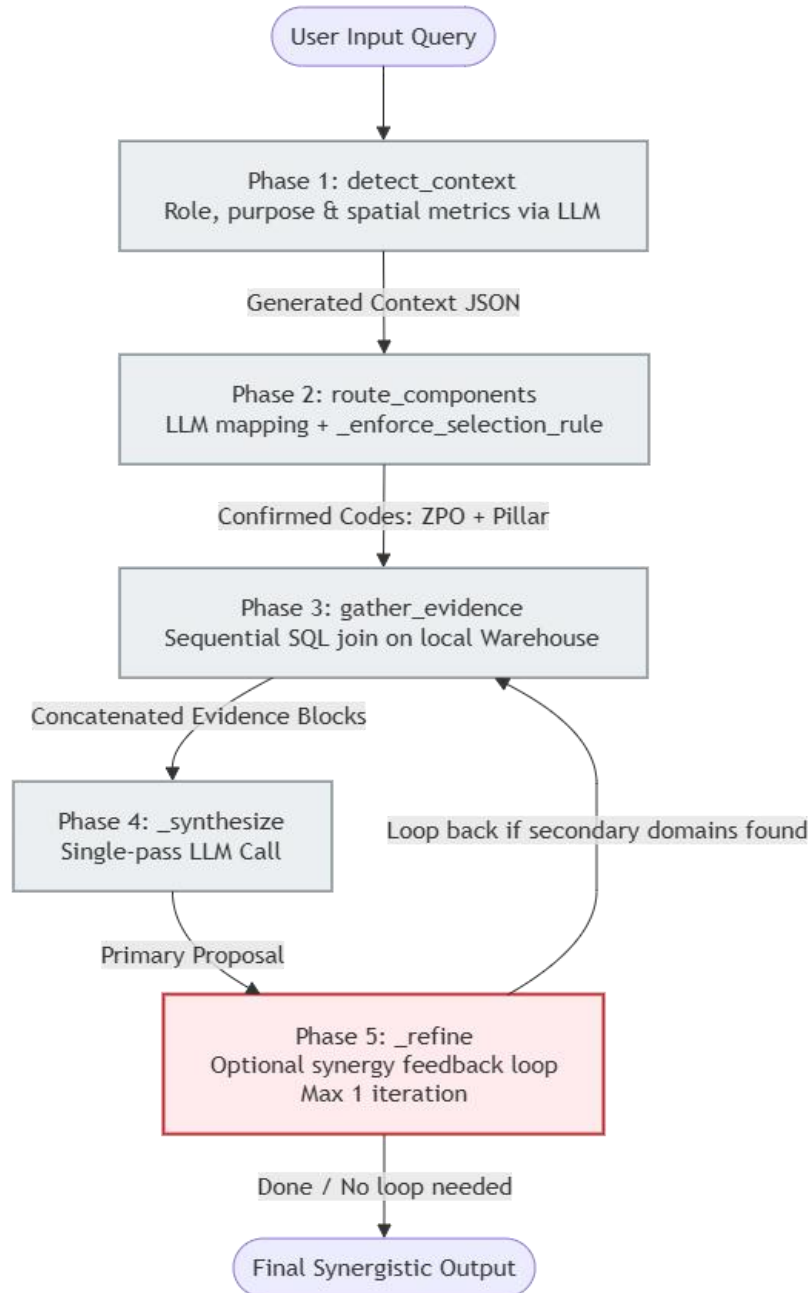
The PoC application utilizes a Python-based analytical engine consisting of specialized controllers for context management, routing, LLM client interactions, and data connectors. To satisfy stringent data privacy requirements, GDPR compliance, and prevent data leakage to commercial third parties, the backend and LLM hosting are deployed on the secure e-INFRA CZ research infrastructure [1]. The OpenAI-compatible LLM endpoint is hosted on a secure academic cloud using runtime-determined model mappings, guaranteeing that all processed municipal queries and local datasets remain strictly within an audited and secure boundary.

To maintain strict network isolation and data sovereignty, the application avoids live REST API calls to external IDP servers during execution. Instead, a localized data connector (`idp_client.py`) triggers secure subprocess scripts to query a local SQL Warehouse containing curated municipal budgets, sociodemographic statistics, and development policies. Fetched JSON payloads are cached in memory using a specialized dictionary-based cache manager to optimize latency and ensure efficient data access without compromising security.

6.4.Execution Pipeline and Sequential Flow

Job state and analysis reports are persisted locally in a SQLite database that contains the analyses and roles tables. To support international dissemination and administrative reporting, the database stores both the primary-language output and an automated English translation. Translation is executed during the final stage of the pipeline via a dedicated LLM call, while temporary exploratory queries bypass database storage.

To operationalize the theoretical methodology within an executable software framework, this section details the mapping of the three conceptual stages (Figure 3, introduced in Section 5.3) into a functional five-phase pipeline (Figure 5). Stage 1 corresponds to automated context recognition (`detect_context`); Stage 2 is executed through component routing (`route_components`) and evidence gathering (`gather_evidence`); and Stage 3 is realized through LLM-based output synthesis (`_synthesize`) and the secondary refinement loop (`_refine`). Processing a municipal query is therefore operationalized as a strictly sequential, five-phase pipeline. Although the system architecture conceptually embeds multi-agent reasoning—achieved through component-specific evidence retrieval from the local warehouse and prompt specialization—it executes these operations sequentially on a single thread rather than via autonomous, parallel agents. In the PoC/MVP setting, this deterministic design choice directly supports system stability, full process traceability, and audited data ingestion, aligning with public sector requirements.”

Figure 5. The final pipeline for the PoC

Source(s): Authors'elaboration, 2026

Phase 1: Context Recognition (detect_context). Under the hood, this phase operationalizes the Recognize Diamond by treating the unstructured natural-language input as a set of observed linguistic manifestations of latent real-world Items. For example, when a municipal representative inputs a phrase such as “establish a community composting facility and introduce bio-waste sorting,” the system does not merely parse the text for keywords. Instead, it treats terms such as “composting facility” and “bio-waste” as concrete linguistic manifestations of underlying municipal management Items.

A specialized “thinker” Large Language Model (deepseek-v4-flash-thinking) extracts and maps these manifestations into a structured five-dimensional context schema. This schema captures the user role, the strategic purpose of the request, the spatial environment, the target municipality, and a normalized query summary. The phase therefore acts as a linguistic-to-cognitive converter: it transforms an unstructured municipal narrative into a formal

representation of the problem space. If a contextual variable is missing from the input, the system assigns the value “unspecified” and continues, which prevents the workflow from failing because of incomplete user input.

Phase 2: Component Routing (route_components). In this phase, the system performs context estimation by evaluating the structured context schema against the national SMART Concept. Individual SMART components function as high-level contextual categories. The routing engine, based on the same LLM model (deepseek-v4-flash-thinking), uses the logic of the Category-Item Connection, which can be represented as a probability vector: $v = (\text{Item}, \text{Category}, P)$, where $P \in [0, 1]$ represents the estimated confidence that an observed Item belongs to a specific SMART component within the recognized municipal context.

For example, in an illustrative composting scenario, the routing process may produce CI-connection candidates such as $v_1 = (\text{“bio-waste”, “C3 (Green and Blue Infrastructure)”}, P = 0.9)$, $v_2 = (\text{“composting facility management”, “ZPO1 (Digital Public Administration)”}, P = 0.7)$, and $v_3 = (\text{“organic material heat potential”, “B2 (Energy Security and Partnership)”}, P = 0.4)$. These vectors are illustrative rather than a formal output of the later case study. They show how the routing mechanism can distinguish between dominant contextual associations and weaker candidate overlaps. A weaker CI-connection, such as the possible relation to B2, does not automatically activate the component; it only indicates a potential direction for later refinement if additional evidence justifies it.

To support administrative validity, the LLM router's probabilistic output is checked by a deterministic validator. This validator ensures that the selected component set respects the methodology's multicontextual boundary, particularly the requirement to combine an overarching governance-related component with at least one pillar-specific component whenever justified by the query.

Phase 3: Evidence Gathering (gather_evidence). For each confirmed component code, the system sequentially retrieves evidence from the local warehouse. This includes the formal component description, target parameters, and relevant examples of good practice linked to the active topic. The purpose of this phase is to ground the recommendation in component-specific data rather than relying only on the general knowledge of the LLM.

Phase 4: Synthesis (_synthesize). The gathered evidence blocks are serialized and concatenated into a single structured prompt. This prompt combines the recognized context, selected SMART components, local indicators, component descriptions, and relevant good-practice examples. The synthesis model (deepseek-v4-flash) then generates a cohesive recommendation that links measures, funding pathways, and synergies across the selected components.

Phase 5: Refinement Loop (_refine). The refinement phase (using deepseek-v4-flash-thinking model) checks the synthesized recommendation against the seven SMART principles and searches for unaddressed synergies, conflicts, or trade-offs. If a justified additional context is identified, the workflow returns to evidence gathering for that component and performs an updated synthesis. If no additional justified context is detected, the system finalizes the structured output.

6.5. Operationalization of the Smart City Concept and Multi-Contextuality

The municipalities featured in the following case studies were selected solely to test local contextual variables—such as settlement type, population size, and data availability—within the PoC/MVP prototype. These cases serve purely as demonstrations of processing locally contextualized queries, not as documentation of real-world deployment. To prevent isolated point solutions, the methodology enforces a two-stage multicontextuality constraint: the routing prompt selects 2–3 active components (combining overarching and pillar categories), while a deterministic Python safeguard programmatically injects any missing component types prior to evidence gathering. The PoC/MVP prototype restricts the available component scope to a transparent subset:

- **ZPO1 (Digital Public Administration as a Service to People, Communities, and Entrepreneurs):** Serves as the overarching domain of Czech Smart City methodology. It focuses on transforming authorities into user-centric, transparent institutions through e-Government, digitized workflows, BIM, and sensor networks under strict cybersecurity standards. (Supported by 44 good practice examples for learning).
- **B2 (Citizens and Municipalities/Cities/Regions as Partners or Parts of Energy Suppliers):**
Positioned within Pillar B (Local Economy), it addresses systemic energy transformation, decentralized renewable energy sources (RES), smart grids, and community energy initiatives to transition citizens from passive consumers to active "prosumers". (Supported by 16 well-structured good practice examples).
- **C3 (Green and Blue Infrastructure of Future Cities and Municipalities):**
Embedded in Pillar C (Environment for Life), it establishes nature-based and technical solutions—such as green roofs, rain gardens, and permeable pavements—to mitigate urban heat islands and improve stormwater management. (Supported by 43 good practice examples for learning).

The methodology enforces a two-stage multicontextuality constraint. First, the routing prompt instructs the model to select at least one overarching ZPO component and at least one pillar component from A–C, with a minimum of two and a maximum of three active components. Second, a deterministic Python safeguard checks the selected array and programmatically injects missing component types when necessary. This mechanism establishes a multicontextual baseline before evidence gathering begins, while still allowing the final component set to remain limited to those contexts that are justified by the concrete municipal query.

7. Practical examples

7.1. Community Composting and Bio-Waste Sorting

For this example, we selected the municipality of Ořechov, a smaller municipality of approximately 3,000 inhabitants located near Brno in the South Moravian Region of the Czech Republic, in order to load and test a concrete local context within the PoC/MVP prototype. The case concerns a request to establish a community composting facility and introduce bio-waste sorting, submitted from the role perspective of a mayor.

Phase 1: Input and Context Extraction

The user input query was: "I want to establish a community composting facility and introduce bio-waste sorting in our municipality." The metadata provided were role: Mayor, and municipality: Ořechov – a smaller municipality (3000 inhabitants near Brno, Czech Republic). The context extraction phase generated a structured representation (Figure 6) containing the role, operational-project purpose, unspecified environment, municipality name, and a concise query summary.

Figure 6. Example of input JSON

```
{
  "role": "Mayor / Elected Representative",
  "purpose": "operational_project",
  "environment": "unspecified",
  "municipality": "Orechov",
  "query_summary": "The user wants to establish a community composting
facility and introduce biodegradable waste separation in the
municipality of Orechov."
}
```

Source(s): Authors'elaboration, 2026

Phase 2: Component Routing

The LLM router mapped the context to the available components and identified ZPO1 and C3 as primary targets (Figure 7). ZPO1 captures the digitalization of citizen services, communication, and participation around the composting facility, while C3 covers the establishment of the facility and bio-waste sorting as part of the municipality's green infrastructure.

Figure 7. Example of JSON identifying the most fitting components

```
{
  "primary": [
    {
      "code": "ZPO1",
      "reason": "Digitalization of services for citizens to manage and
provide information about the community composting facility...",
      "confidence": 0.7
    },
    {
      "code": "C3",
      "reason": "Establishment of a community composting facility and
bio-waste separation as part of the green infrastructure of the
municipality.",
      "confidence": 0.9
    }
  ]
}
```

Source(s): Authors'elaboration, 2026

Phase 5: Refinement Loop Triggering

During the refinement stage, the system did not identify any additional components beyond the initially selected ZPO1 and C3. The case, therefore, remained within the two-component interpretation: ZPO1 for digital public administration, citizen communication, and participation, and C3 for green and blue infrastructure related to community composting and bio-waste sorting. If, however, the refinement stage detected a justified overlap with another component, that component would be identified at this point, additional evidence would be gathered for it, and the synthesis process would be repeated with the enriched component set.

Final Structured Output

The final persisted result is structured into six types and provenance-tracked attributes: summary, recommendations (Figure 8), measures, grant frameworks, examples (Figure 9), and

synergies. The output recommends involving citizens in planning and communication, using the compost for public greenery and local climate adaptation, informing citizens through municipal communication channels, and identifying available subsidy and grant programs. The measures are tagged against ZPO1 and C3, allowing the recommendation to remain grounded in the Smart City component framework instead of appearing as a generic chatbot response.

Figure 8. Summary example with specific recommendation for selected municipality

Summary

To establish a community composting facility and biowaste sorting, it is advisable to use participatory approaches that involve citizens in planning and decision-making, which is supported by component ZPO1. Furthermore, it is possible to build on component B2, which emphasizes the use of waste as an energy source and energy self-sufficiency, including through community energy projects. It is recommended to combine awareness-raising, participation, and technical solutions with regard to local conditions.

Recommendations

1. Involve citizens in the planning of the composting facility through participatory meetings and surveys to ensure the project is accepted and effectively used.
2. Consider using biowaste not only for compost but also for energy production (e.g., biogas), thereby building on component B2 and increasing the municipality's energy self-sufficiency.
3. Create an information campaign on proper biowaste sorting and the benefits of community composting, using digital tools and transparent communication (component ZPO1).
4. Explore funding opportunities from European funds that support circular economy and community energy projects.
5. Design a biowaste collection system that is logistically efficient and takes into account local conditions (e.g., collection routes, containers).

Source(s): Authors'elaboration, 2026

Figure 9. Example of the component output equipped with good practice examples links

Evidence from IDP (component agents)

ZPO1 – For municipalities, cities, and regions to function 'smartly', a well-organized public administration based on new communication technologies is needed, providing appropriate services to citizens (informational, interactive, transactional), cooperating with citizens in creating local and regional solutions, functioning well within the office, being transparent in public procurement, and managing its own property as efficiently as possible, based on systematic data collection and using all available tools (BIM, 3D modeling, process automation, and automation of communication, especially towards citizens and the resolution of life situations). Currently, this is included in several strategic government documents (Digital Czechia, Concept of Client-Oriented Public Administration of the Czech Republic 2030), and funds from EU funds are also being allocated for the digitalization and setting of processes in offices. The use of basic public administration registers has become completely common, and support from the MPO for BCO is being implemented to reduce the insufficiency of digital infrastructure. However, it still holds that especially self-government lacks sufficient information or knowledge in this area, and the lack of IT specialists in the public sector is quite evident. For this reason too, it is necessary to support vertical and horizontal cooperation of public administration and the possibility of shared solutions between the state, regions, and municipalities. Given that municipalities also perform state administration in delegated competence, it is essential that state administration also functions well and its electrification proceeds systematically, predictably, and in a planned manner with the participation of experts from municipalities and regions. It is therefore necessary that local IT solutions proceed as uniformly and standardly as possible.

- [MAS Pomalší: Study of the Kaplicko region: "How to bring the countryside and young people back into the game"](#) · Communication between public administration, citizens, and other entities, participation
- [Jeseník: The future form of Freedom Square is being created with public participation](#) · Communication between public administration, citizens, and other entities, participation; Planning and management system, incl. urbanism and revitalizations, spatial planning and regional development
- [Turnov: Presentation of the city's new visual identity](#) · Communication between public administration, citizens, and other entities, participation
- [Prague 21: Q&A: Ask, the municipal district leadership will answer](#) · Communication between public administration, citizens, and other entities, participation
- [Jeseník: We know the winners of the 4th year of Tvoříme Jeseník](#) · Communication between public administration, citizens, and other entities, participation
- [Jeseník: Good ideas of residents are becoming reality. First as 'Hafpark'](#) · Communication between public administration, citizens, and other entities, participation

Source(s): Authors'elaboration, 2026

7.2. Building Optical Infrastructure for Smart Municipal Services

While the previous case demonstrates that the PoC/MVP prototype can remain limited to two justified components when no further overlap is detected, a second case is useful for showing the full routing capacity of the available component scope. For this case study, we selected the municipality of Kuřim, a medium-sized town of approximately 11,860 inhabitants located near Brno in the South Moravian Region of the Czech Republic, in order to load and test a more

complex local context. The case illustrates a situation in which the same orchestration mechanism activates all three currently implemented components: ZPO1, B2, and C3.

Phase 1: Input and Context Extraction

The scenario concerns the municipality of Kuřim and is submitted from the role perspective of an innovation broker. The purpose is classified as an operational project, the environment is specified as the municipality of Kuřim, and the municipality field is also set to Kuřim. The query summary states that the user is seeking advice on how to link an optical infrastructure project with other municipal areas and where to find inspiration, including possible visits to examples of good practice for mayors. This input is particularly suitable for testing the full PoC/MVP scope because optical infrastructure can function simultaneously as a digital backbone, an enabler of smart energy management, and a data-collection layer for environmental monitoring.

Phase 2: Component Routing

The component routing phase identifies ZPO1, B2, and C3 as relevant to the query. ZPO1 is activated because the optical network can support the digitalization of public administration, including e-government services, participatory budgeting, open data, citizen communication, and more efficient management of municipal assets. B2 is activated because the same infrastructure can enable smart management of public lighting, building heating, consumption metering, and integration of renewable energy sources. C3 is activated because the network can also serve as a communication layer for sensors monitoring air quality, noise, soil moisture, and the condition of watercourses, thereby supporting green and blue infrastructure planning. Unlike the Ořechov case, where the final component set remains limited to ZPO1 and C3, this scenario directly activates the full currently implemented prototype scope.

Proposed Measures Across Components

An important feature of this case is that the system does not merely classify the optical network under three component labels. In the Proposed measures section, it automatically translates the same infrastructure investment into component-specific municipal uses and attaches relevant examples of good practice (Figure 10) to support each direction. The optical network is therefore interpreted as an enabling platform: for ZPO1 it becomes a backbone for digital public services and citizen communication; for B2 it becomes a communication layer for smart energy management; and for C3 it becomes an infrastructure for environmental sensing and green-blue planning.

- **Optical network as the backbone of a smart city (ZPO1):** Building optical infrastructure that connects the municipal office, schools, libraries, and other public buildings, enabling digital services for citizens, participatory budgeting, and more efficient asset management.
- **Smart energy management using the optical network (B2):** Installing sensors and control systems for public lighting, building heating, and energy-consumption monitoring, with communication through the optical network and support for savings and integration of renewable sources.
- **Environmental monitoring via the optical network (C3):** Deploying sensors for air quality, noise, soil moisture, and watercourse monitoring, with data transmitted through the optical network to support green and blue infrastructure planning.

In each of these directions, the system connects the proposed use of the network with examples of good practice retrieved from the evidence layer, so that the recommendation is not only technically plausible but also grounded in comparable municipal experience. The output also recommends involving citizens in project planning so that the network is dimensioned for future needs such as IoT and smart applications and remains open to other entities. Relevant funding frameworks include the Integrated Regional Operational Programme (IROP), specifically for digital infrastructure, the Operational Programme Technology and Applications for

Competitiveness (OP TAK), which supports digital technologies, and the National Recovery Plan, especially its digital transformation component.

The summary generated for this case explicitly frames the optical infrastructure project as a shared municipal platform. In this interpretation, the optical network is not treated merely as a telecommunications investment, but as a backbone for smart-city development: it can support digital public services, provide the communication infrastructure for smart energy management, and enable spatial and environmental data collection for planning and maintenance. This illustrates how the PoC/MVP prototype converts a broad municipal question into a structured, component-tagged set of measures and funding pathways.

Figure 10. Good practice examples and synergies summary

Examples of good practice from IDP

[MAS Pomalší: Kaplicko Study](#) · ZPO1

[Jeseník: The future appearance of Freedom Square is being created with public participation](#) · ZPO1

[Rudíkov: A small municipality uses renewable energy and smart technologies](#) · B2

[Jihlava: Smart management of the wastewater treatment plant](#) · C3

Synergies

- Optical infrastructure (ZPO1) enables data collection and transmission for smart energy management (B2), leading to savings and more efficient use of resources.
- Sensors connected to the optical network (ZPO1) can monitor the condition of greenery and water bodies (C3), supporting climate change adaptation.
- Digitalisation of the office (ZPO1) can use data from energy and environmental sensors (B2, C3) for better planning and decision-making.

Source(s): Authors'elaboration, 2026

Figure 11. Summary and recommendation based on three components

Role: innovation broker · **Purpose:** operational_project · **Environment:** municipality of Kuřim · **Municipality:** Kuřim

Query summary: The user is seeking advice on how to link an optical infrastructure project with other areas and where to find inspiration, possibly recommending visits to examples of good practice for mayors.

Component routing

ZPO1, B2, C3

Summary

The optical infrastructure project in the municipality of Kuřim can be linked with the digitalisation of public administration (component ZPO1), energy (component B2), and green/blue infrastructure (component C3). We recommend leveraging synergies between these areas, e.g., the optical network as a backbone for smart energy management or data collection for spatial planning. Inspiration can be drawn from examples of good practice that show how municipalities engage citizens and modern technologies.

Recommendations

1. Link the optical infrastructure with the digitalisation of the municipal office (ZPO1) – use it for e-government, participatory budgeting, and open data.
2. Consider synergy with energy (B2) – the optical network will enable smart management of public lighting, consumption metering, and integration of renewable sources.
3. Use the optical network for sensors within green/blue infrastructure (C3) – e.g., monitoring air quality, soil moisture, or the condition of watercourses.
4. Draw inspiration from examples of participation (ZPO1) – involve citizens in project planning so that the network is used for their needs.
5. Ensure that the optical infrastructure is dimensioned for future needs (e.g., IoT, smart applications) and is open to other entities.

Source(s): Authors'elaboration, 2026

7.3.Demonstration of Added Value

To demonstrate the added value of context recognition and evidence gathering, the PoC/MVP prototype includes a comparative baseline benchmark. Users can submit the same raw query directly to a standard conversational AI interface through the “Ask AI without context” module.

The comparison is not intended merely to show that the PoC/MVP prototype produces a longer or more detailed answer than a generic chatbot. Rather, it evaluates whether the response becomes more specific, more evidence-grounded, and more explicitly aligned with the seven SMART principles introduced in Section 2.2.

The principle of evidence-based governance is strengthened in both cases because the output is organized into context, components, recommendations, measures, funding frameworks, and synergies rather than remaining a free-form text response. The system therefore provides not only a narrative answer, but an auditable decision-support structure. Municipal actors can inspect why a component was selected, what evidence supports it, which measures follow from it, and how the resulting proposal relates to the SMART framework.

A generic chatbot can produce plausible advice, but it typically remains conversational and sectorally shallow. It may list reasonable actions, but it does not determine which SMART components are justified, does not distinguish between measures and funding pathways, and does not evaluate whether a second or third municipal context should enter the decision-support process. By contrast, the CESMOD AI Flow identifies the relevant set of components, gathers structured evidence, tags recommendations by component, and checks the output against multi-contextual SMART logic.

The added value of the PoC/MVP prototype therefore lies not only in producing longer or more detailed text, but in transforming an unstructured municipal query into a SMART-principle-aware decision-support object. Such an object is more concrete, more grounded in data, and more transparent for expert review. This supports the paper's central argument: an AI-driven municipality requires context-aware orchestration, not merely a conversational chatbot interface.

8. Discussion

The empirical evaluation of the AI Flow for Municipalities demonstrates the feasibility of transitioning from opaque, single-context conversational portals toward a context-aware, evidence-grounded decision-support architecture. By anchoring Large Language Model reasoning directly within the 16 functional components and seven governing principles of the Czech national Smart Cities Concept (Ministry for Regional Development, 2021) and coupling it with curated evidence from the Information and Data Platform (IDP / WP2), the pipeline mitigates algorithmic hallucinations and the "black box" phenomenon. Nevertheless, several critical MVP-stage limitations must be addressed within the broader CESMOD research roadmap.

Structurally, the prototype's functional scope was deliberately restricted to three representative components (ZP01: Digital Public Administration, B2: Energy Efficiency, and C3: Green/Blue Infrastructure). While sufficient for testing complex multi-contextual overlaps, cross-domain routing, and deterministic Python safeguards (`_enforce_selection_rule`), this reduced scope does not fully reflect the dense, multi-sectoral realities of municipal administration. A single municipal event—such as bio-waste management or optical infrastructure—inherently spans multiple domains, requiring the AI to evaluate cross-domain synergies rather than optimizing in sectoral silos. As the system expands to the remaining 13 national components (e.g., inclusive housing, mobility), evaluating probabilistic vectors $\mathbf{v} = (\text{Item}, \text{Category}, P)$ across an expanded category space will introduce significant complexity, requiring further assessment of LLM reasoning precision without prompt confusion.

Operationally, the evidence base within the IDP bounds the system's capacity to recognize multi-contextual manifestations. The Recognize Diamond logic relies on expert-annotated Good Practice Examples; sparse domain annotations cause confidence scores ($P \in [0, 1]$) to drop toward zero, triggering fallback routing rather than multi-contextual alignment. Furthermore, the current single-pass execution pipeline omits interactive, multi-turn clarification dialogs. When queries are incomplete, the system assigns default parameters (e.g., "unspecified" spatial boundaries) to maintain pipeline stability, limiting its ability to resolve ambiguous administrative requests through conversational disambiguation.

Empirically, current findings rely on synthetic case studies (Ořechov, Kuřim). Comprehensive Quadruple Helix field testing across distinct user roles—such as mayors needing high-level grant alignment, regional innovation brokers (SMARTNET.cz / WP3) requiring granular, multi-sectoral trade-off analyses, or central ministry gestors tracking indicators—is essential for evaluating real-world administrative utility. Institutionally, automated decision support must never replace human administrative discretion. Maintaining a strict "human-in-the-loop" framework—supported by brokers (WP3) and capacity building via the SMART Academy (WP4)—ensures civil servants critically evaluate generated recommendations while retaining full legal accountability. Future technological developments will focus on scaling the local warehouse into a read-only API connection with national open-data repositories, incorporating dense vector embeddings alongside probabilistic LLM routing, and implementing parallel execution threads for evidence gathering to optimize latency across the complete Smart Cities Concept.

9. Conclusion

This study has demonstrated the practical feasibility of transitioning from opaque, single-context portals to an explainable, auditable decision-support architecture for public administration. Evaluated within the research ecosystem of the CESMOD project, the AI Flow for Municipalities operationalizes Evidence-Based Policy by making underlying data, contextual routing, and cross-sectoral synergies fully transparent. Consequently, local stakeholders—from mayors to regional innovation brokers—can clearly trace the rationale behind AI recommendations, see how municipal datasets are utilized, and harness intelligent tools within daily administrative workflows. Ultimately, this pilot offers a scalable model for context-aware governance, providing methodological inspiration for international public administrations seeking sustainable, resilient, and human-centered digital transformation..

A primary advantage of this architecture in the Czech Republic is its alignment with the long-term, holistic framework of the Smart Cities Concept and its Implementation Plan. By directly embedding this national policy framework and its 16 functional components into the AI orchestration pipeline—backed by the expert-curated repository of the Information and Data Platform (IDP)—the system bridges the gap between high-level governmental strategy and local execution. Built upon a stable national foundation, this approach holds significant promise for driving genuine, data-driven territorial development across Czech municipalities of all sizes.

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