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AI and Smart City: Smart Technologies for Future Cities – An Analysis of Italian and European Projects"

TESI DI LAUREA MAGISTRALE IN MANAGEMENT ENGINEERING INGEGNERIA GESTIONALE

Author: **Fatemeh Ahmadi**

Student ID: 245306
Advisor: Prof. Luca Gastaldi
Co-advisor: Dr. Camilla Scarpino
Co-advisor: Dr. Maria Vittoria Scarcia
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Abstract

As rapid urbanization intensifies challenges related to mobility, environmental sustainability, and public service provision, cities increasingly rely on digital and data-driven solutions. In parallel, the accelerated development of Artificial Intelligence (AI) has become a key enabler of smart city initiatives worldwide. This thesis explores the current state of the art in the application of AI within smart city projects, to systematically analyze their objectives, methodological characteristics, and areas of application. The research adopts a structured methodological framework that combines a comprehensive literature review with the creation of a dedicated database of AI-enabled smart city projects implemented between 2023 and 2025 across multiple countries. This database supports a qualitative and comparative analysis of projects based on smart city domains, application scope, and technical intensity, enabling the identification of patterns and trends in contemporary AI adoption. The analysis indicates that AI deployment in smart cities exhibits a clear domain-oriented specialization, with projects differing significantly in terms of technical complexity, integration level, and functional focus. The classification of applications into lightweight versus intensive and narrow versus broad categories highlights the heterogeneous nature of current implementations and reflects the influence of data availability, operational constraints, and policy objectives on technological choices. At the conclusion of the analysis, it becomes possible to understand the current state of smart city projects as well as the emerging challenges associated with scaling these projects toward broader domains and developing an integrated ecosystem that encompasses all components of a city and enables a reliable, data-driven urban environment.

Keywords: Smart City, Artificial Intelligence, Urban Planning, Urban Digital Innovation

Abstract In Italian

Poiché la rapida urbanizzazione intensifica le sfide relative alla mobilità, alla sostenibilità ambientale e all'erogazione dei servizi pubblici, le città si affidano sempre più a soluzioni digitali e basate sui dati. Parallelamente, lo sviluppo accelerato dell'Intelligenza Artificiale (IA) è diventato un fattore abilitante fondamentale per le iniziative di *smart city* in tutto il mondo. Questa tesi esplora l'attuale stato dell'arte nell'applicazione dell'IA all'interno dei progetti di *smart city*, al fine di analizzarne sistematicamente gli obiettivi, le caratteristiche metodologiche e le aree di applicazione.

La ricerca adotta un quadro metodologico strutturato che combina una revisione completa della letteratura con la creazione di un database dedicato di progetti di *smart city* basati sull'IA, implementati tra il 2023 e il 2025 in diversi paesi. Questo database supporta un'analisi qualitativa e comparativa dei progetti basata sui domini delle *smart city*, sull'ambito di applicazione e sull'intensità tecnica, consentendo l'identificazione di modelli e tendenze nell'adozione contemporanea dell'IA.

L'analisi indica che l'implementazione dell'IA nelle *smart city* mostra una chiara specializzazione orientata al dominio, con progetti che differiscono significativamente in termini di complessità tecnica, livello di integrazione e focus funzionale. La classificazione delle applicazioni nelle categorie *lightweight* (leggere) rispetto a *intensive* (intensive) e *narrow* (limitate) rispetto a *broad* (ampie) evidenzia la natura eterogenea delle attuali implementazioni e riflette l'influenza della disponibilità dei dati, dei vincoli operativi e degli obiettivi politici sulle scelte tecnologiche.

In conclusione, dell'analisi, diventa possibile comprendere lo stato attuale dei progetti di *smart city*, nonché le sfide emergenti associate alla scalabilità di questi progetti verso domini più ampi e allo sviluppo di un ecosistema integrato che comprenda tutte le componenti di una città e permetta la realizzazione di un ambiente urbano affidabile e guidato dai dati.

Keywords: Smart City, Intelligenza Artificiale, Tecnologia Intelligente, Innovazione Digitale Urbana

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1.Introduction

This chapter provides an overview of two concepts which are the Smart City and the role of Artificial Intelligence (AI) as one of its keys in enabling technologies. It first explores AI in depth, examining its capabilities, its integration with other digital infrastructures, its growing influence on urban transformation, and the challenges they aim to address the chapter then introduces the fundamental principles of smart cities, including their objectives and technological foundations, by analyzing how smart cities have evolved over time and how AI continues to shape their development. As shown in figures 1 and 2, this chapter offers a structured foundation for understanding the current landscape of AI-driven urban innovation. The following scheme outlines the main topics covered in this chapter:

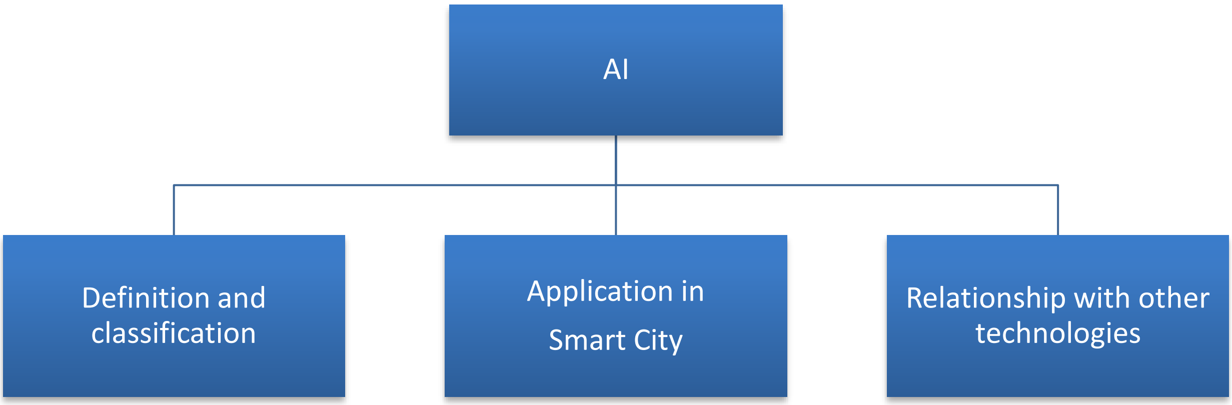


Figure 1: Introduction - AI

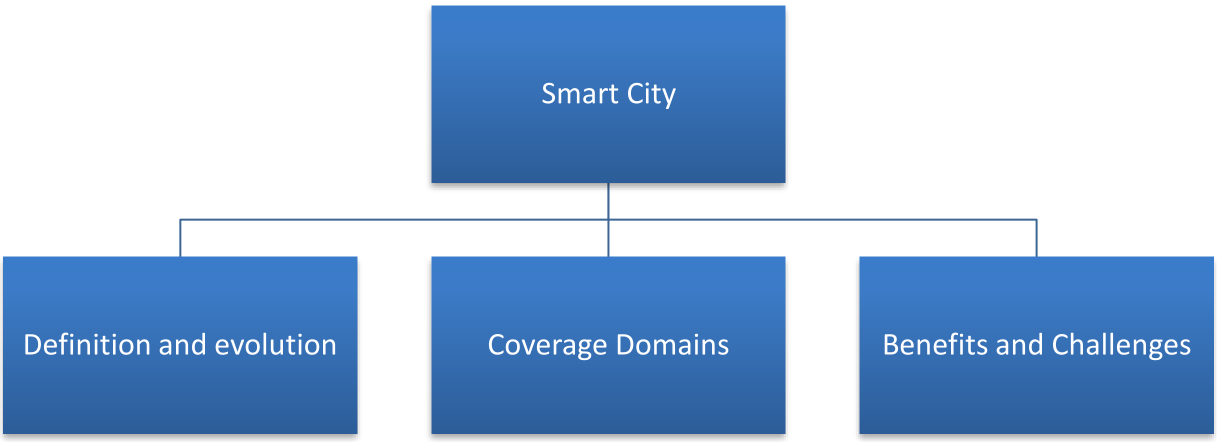


Figure 2: Introduction - Smart City

The world is experiencing an unprecedented wave of urbanization, fundamentally reshaping how societies organize, function, and evolve. As of 2024, over half of the global population resides in urban areas, a figure projected to reach 68% by 2050. This rapid urban expansion brings both extraordinary opportunities and challenges—from mounting environmental pressures and resource scarcity to escalating demands for efficient infrastructure and equitable public services. In response to these multifaceted urban challenges, the concept of smart cities has emerged as a transformative paradigm, leveraging digital technologies to create more sustainable, efficient, and livable urban environments.[1][2]

At the heart of this urban transformation lies Artificial Intelligence (AI), which has evolved from a theoretical concept to a pivotal enabling technology to reshape every side of city life. AI's capabilities, spanning machine learning, deep learning, natural language processing, and computer vision—are revolutionizing how cities collect, analyze, and act upon vast streams of urban data. By integrating AI with complementary technologies such as the Internet of Things (IoT), big data analytics, and digital infrastructure, smart cities are transitioning from reactive management systems to proactive, data-driven ecosystems capable of anticipating needs, optimizing resources, and enhancing quality of life for all residents.

1.1. Artificial Intelligence

In parallel with the evolution of digital connectivity and automation, Artificial Intelligence (AI) has emerged as a fundamental technology shaping modern computational systems. AI refers to the capability of machines and software systems to perform tasks that traditionally require human intelligence, such as learning, reasoning, perception, and decision-making. Unlike conventional software, which operates through explicitly programmed instructions, AI systems are designed to adapt, infer, and improve their performance by processing large volumes of data. This shift from rule-based automation to data-driven intelligence represents a significant step in the evolution of technology, enabling systems not only to execute predefined tasks but also to respond dynamically to complex and changing environments.

The global AI in smart cities' market size is USD 50.63 billion in 2025. It is expected to grow from USD 64.71 billion in 2026 to about USD 460.47 billion by 2034, with strong annual growth over this period. This growth represents a compound annual growth rate (CAGR) of 27.80% between 2025 and 2034. The demand for sustainable and efficient urban solutions drives the market. The growing focus on improving the quality of city life and regulatory compliance is driving the use of artificial intelligence in smart city services.[1]

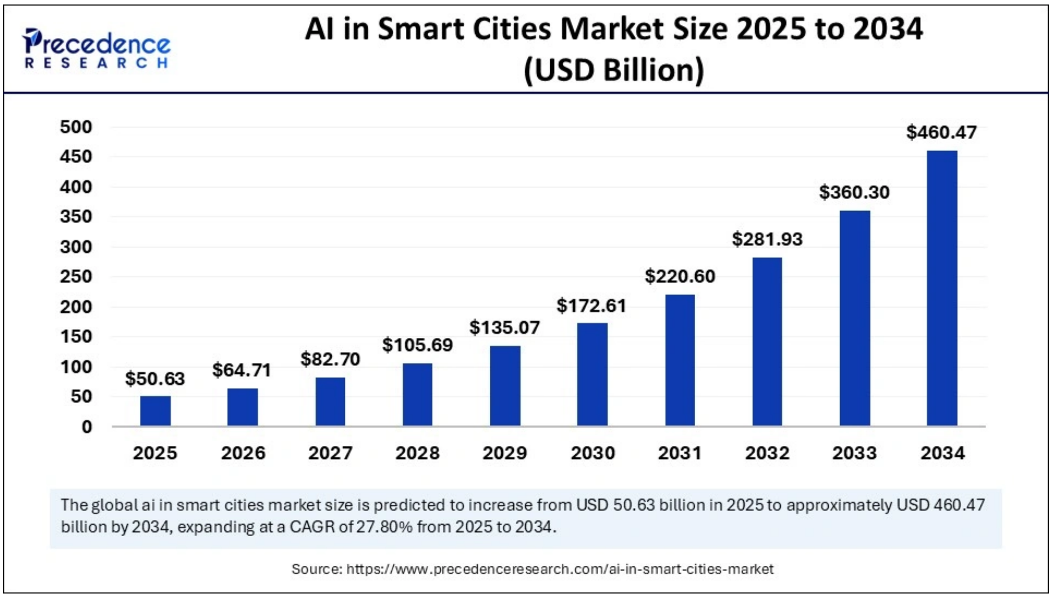
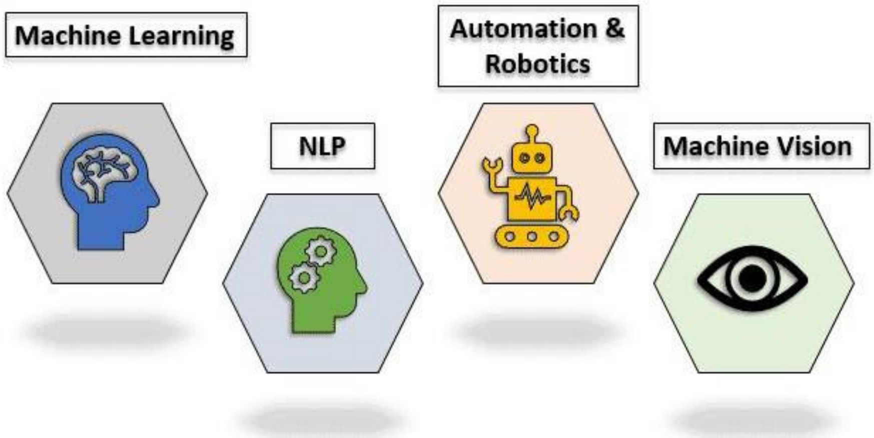


Figure 3: AI in smart city Market size 2025- 2034

[1] https://www.precedenceresearch.com/ai-in-smart-cities-market

1.1.1. Technique of Artificial Intelligence



Artificial Intelligence techniques refer to a set of methods and algorithms used to develop intelligent systems that can perform tasks requiring human-like intelligence. Some of the widely used ones are:

- **Machine Learning**
- **Natural Language Processing**
- **Computer Vision**
- **Deep Learning**
- **Data Mining**
- **Robotics**

- Machine Learning (ML)

Machine Learning (ML) forms the foundation of contemporary AI systems. ML employs statistical algorithms that enable computers to learn from data and make predictions or decisions without explicit programming.

1. Unsupervised machine learning - AI systems analyze unlabeled data, where no predefined outcomes are provided. The objective is to uncover inherent structures or patterns within the data without any prior knowledge. For instance, it can group similar customer behavior data to identify customer segments for targeted marketing strategies.

2. Supervised learning - A combination of an input data set and the intended output is inferred from the training data. AI systems learn from a labelled dataset, where each data point is associated with a known outcome. For instance, it enables email spam filters to distinguish between spam and legitimate emails based on learned patterns.

3. Semi-supervised learning - It is a method that uses a small amount of labelled data and a large amount of unlabeled data to train a model. The goal of semi-supervised learning is to learn a function that can accurately predict the output variable based on the input variables, like supervised learning. However, unlike supervised learning, the algorithm is trained on a dataset that contains both labelled and unlabeled data.

4. Reinforcement learning - In RL, the data is accumulated from machine learning systems that use a trial-and-error method to learn from outcomes and decide which action to take next. After each action, the algorithm receives feedback that helps it determine whether the choice it made was correct, neutral or incorrect. It performs actions with the aim of maximizing rewards, or in other words, it is learning by doing to achieve the best outcomes.

In urban contexts, ML algorithms analyze historical patterns—such as traffic flows, energy consumption, or crime statistics—to forecast future trends and optimize resource allocation. [3]

- **Natural Language Processing (NLP)**

Natural Language Processing (NLP) focuses on enabling computers to understand, interpret, and generate human language in order to support effective interaction between people and machines. This task is challenging because human languages are complex, flexible, and governed by many implicit rules. NLP addresses these challenges by using algorithms that identify and model linguistic patterns, transforming unstructured language data into forms that computers can process and analyze. In smart cities, AI techniques have paved the way for virtual assistants, chatbots, and language translation tools, making communication between humans and machines [4]

- **Deep Learning (DL)**

A specialized subset of ML utilizes artificial neural networks inspired by the human brain's structure. These networks consist of multiple interconnected layers that progressively extract higher-level features from raw data. DL excels at processing complex, unstructured data such as images, video, and audio, making it invaluable for applications like computer vision in autonomous vehicles, facial recognition in public safety systems, and satellite imagery analysis for urban planning. [4][6]

- **Computer Vision**

Computer vision is a key technique within the study of artificial intelligence that focuses on enabling machines to perceive, analyze, and understand visual information from images and videos. By applying algorithms drawn from machine learning and deep learning, computer vision systems extract meaningful features from visual data and use them to perform tasks such as image classification, object detection, segmentation, and motion analysis. These techniques allow artificial intelligence systems to interpret complex visual environments and make informed decisions, supporting a wide range of applications in fields such as healthcare, autonomous systems, surveillance, and human–computer interaction.

- **Data mining**

This is the process of extracting knowledge or insights from large amounts of data using various statistical and computational techniques. The data can be structured, semi-structured, or unstructured, and can be stored in various forms such as databases, data warehouses, and data lakes.

The primary goal of data mining is to discover hidden patterns and relationships in the data that can be used to make informed **decisions or predictions**. This involves exploring the data using various techniques such as clustering, classification, regression analysis, association rule mining, and anomaly detection.

Data mining has a wide range of applications across various industries, including marketing, finance, healthcare, and telecommunications. For example, in marketing, data mining can be used to identify customer segments and target marketing campaigns, while in healthcare, it can be used to identify risk factors for diseases and develop personalized treatment plans.

However, data mining also raises ethical and privacy concerns, particularly when it involves personal or sensitive data. It's important to ensure that data mining is conducted ethically and with appropriate safeguards in place to protect the privacy of individuals and prevent misuse of their data. [6]

- Robotics & Automation

Automation aims to enable machines to perform boring, repetitive jobs, increasing productivity and delivering more effective, efficient, and affordable results. To automate processes, many businesses employ machine learning, artificial neural, and graphs. By leveraging the CAPTCHA technique, this automation can avoid fraud problems during online payments. Robotic process automation is designed to carry out high-volume, repetitive jobs while being capable of adapting to changing conditions.

These AI technologies do not operate in isolation. Their integration creates powerful synergies that amplify their individual capabilities, enabling smart cities to address urban challenges with unprecedented sophistication and scale.[4][5][6]

1.1.2. AI Applications in Smart Cities: Transforming Urban Domains

AI has moved beyond theoretical promise to become an operational reality across numerous urban sectors, delivering measurable improvements in efficiency, sustainability, and quality of life. This section examines how AI is deployed across smart city domains, demonstrating its transformative impact through evidence-based examples and case studies.

1- Smart Mobility and Transportation

AI is fundamentally transforming urban mobility by optimizing traffic flow, enabling autonomous systems, and revolutionizing public transit operations. These applications address some of cities' challenges: congestion, emissions, and accessibility.

- **Traffic Management and Optimization**

AI-powered traffic management systems analyze real-time data from multiple sources—road sensors, GPS devices, traffic cameras, and connected vehicles—to dynamically adjust traffic signals, predict congestion patterns, and optimize flow across entire urban networks. Pittsburgh's AI traffic light system achieved remarkable results: a 25% reduction in travel times and a 40% decrease in idling time, significantly cutting emissions. These systems continuously learn from traffic patterns, adapting their responses to minimize delays and maximize throughput.
Singapore's Intelligent Transport System, part of the Smart Mobility 2030 initiative, exemplifies comprehensive AI integration in urban mobility. The system utilizes AI and real-time data analytics to monitor and control traffic flow throughout the city-state. AI-powered traffic prediction models adjust signals based on current and forecasted volumes, optimizing bus routes and enhancing pedestrian safety.[7][8]

- **Autonomous Vehicles and Shared Mobility**

The integration of autonomous vehicles represents the future frontier of urban mobility. Baidu's Apollo Go robotaxi service in Wuhan has completed over 7 million rides with zero major accidents, demonstrating the technical feasibility and reliability of fully

autonomous fleets at scale. These AI-driven vehicles use computer vision and sensor fusion—integrating data from LiDAR, radar, and cameras—to interpret surroundings and navigate safely alongside human drivers.
AI also optimizes first-mile and last-mile connectivity, the critical links between transit hubs and final destinations. By assessing demand density, terrain, weather conditions, and multimodal connection availability, AI enables efficient planning of shared mobility solutions such as e-scooters, bike-sharing programs, and autonomous shuttles. Mozee's electric autonomous shuttles in Dallas provide on-demand, zero-emission transport in controlled environments, reducing reliance on private vehicles and easing congestion in dense urban areas.[7]

- **Demand-Responsive Public Transit**

Traditional public transportation operates on fixed schedules that cannot adapt to fluctuating demand. AI-enabled demand-responsive transit systems revolutionize this model by adjusting routes and schedules based on real-time passenger needs rather than static timetables. Machine learning algorithms analyze passenger demand patterns, traffic conditions, vehicle sensor data, and city camera feeds to optimize bus and train schedules, minimize wait times, and elevate service quality. This approach not only reduces operational costs but also improves accessibility for underserved areas, making public transit more equitable and efficient.

- **Predictive Fleet Maintenance**

Fleet operators—from public buses to logistics vehicles—face substantial costs from unplanned breakdowns and service disruptions. AI-enabled predictive maintenance uses telematics, sensor data, and historical repair logs to forecast component failures before they occur. This proactive approach schedules maintenance during low-demand periods, keeping assets operational and extending vehicle lifespans while reducing costs. The technology has proven particularly effective in maintaining the reliability of public transit systems, where downtime directly impacts thousands of commuters.

2- Smart Lighting Systems

Smart street lighting powered by AI has emerged as a high-impact domain for municipal energy savings and grid flexibility. Modern systems use LED technology that consumes 50–70% less power than conventional sodium vapor lamps, and when combined with AI-driven adaptive control, deliver comprehensive operational benefits.

AI algorithms analyze traffic patterns, weather conditions, pedestrian activity, and historical data to dynamically adjust lighting output. Motion-activated systems increase illumination when movement is detected, while time-based dimming reduces intensity during off-peak hours. Weather-responsive adjustments brighten lights during fog or heavy rain to maintain safety.

A Turkish organization's pilot deployment on Greece's most strategic motorway exemplifies real-world impact, delivering 60–80% energy savings compared to conventional sodium vapor systems when combined with LED conversion, while simultaneously reducing CO_2 emissions and improving traffic safety. Sound-sensing adaptive streetlamps represent emerging innovation, using AI to classify environmental sounds (traffic type, weather events, emergency alerts) and adjust lighting dynamically while gathering citywide environmental intelligence.

Predictive maintenance systems use anomaly detection on current and voltage patterns to identify failing luminaires before they create safety hazards or require expensive emergency repairs, extending infrastructure lifespan and reducing maintenance costs.[9][10]

3- Waste Management Optimization

AI-enabled waste management systems demonstrate how data-driven optimization can simultaneously reduce environmental impact and municipal costs. IoT sensors embedded in smart bins continuously transmit fill-level data to centralized platforms where machine learning models predict overflow events and optimize collection routes in real time.
A comprehensive Frontiers in Sustainability study demonstrates the quantifiable impact: AI-IoT systems using XGBoost classifiers for overflow prediction, combined with spatial risk mapping and graph-theoretic routing optimization, achieved 94.1% predictive accuracy and 95.8% recall in identifying overflow-prone bins. Compared to static collection schedules, these smart systems reduced overflow events by 50%, missed pickups by 72.7%, fuel consumption by 15.5%, while improving bin utilization efficiency by 35.5%. Fixed collection schedules typically result in annual cost increases of 70% due to unnecessary pickups, while inefficient routing increases carbon footprint by 50%, challenges that AI directly addresses through dynamic optimization.[11][12]

Machine learning models forecast waste generation patterns by neighborhood, season, and anticipated events (festivals, weather events, demographic changes), enabling cities to right-size fleet capacity and contracts more efficiently. Computer vision systems at transfer stations and materials recovery facilities automate waste sorting and recyclable identification, improving recycling rates while reducing manual labor costs.

4- AI-Driven Land Management and Spatial Planning

AI-enhanced environmental monitoring systems address urban air quality, land-use optimization, and climate adaptation challenges through integrated real-time monitoring and predictive modeling. Deep learning-based air quality forecasting systems outperform traditional statistical methods by capturing complex nonlinear relationships between meteorological variables, traffic patterns, industrial emissions, and pollutant concentrations.

Beijing's partnership with IBM to deploy the Green Horizon project demonstrates strategic application of AI for air quality management. The system utilizes networked sensors combined with weather data and pollution source information to create highly accurate air quality forecasts, enabling proactive interventions including traffic flow adjustments and industrial emission controls before hazardous levels are reached.

The BREATHE system, developed for UAE urban environments, integrates real-time monitoring with machine learning-based forecasting using GeoAI techniques. Random Forest models achieve up to 98.2% accuracy in predicting multiple pollutants ($PM_{2.5}$, PM_{10}, SO_2, CO, NO_2, O_3) by integrating ground-level measurements with satellite imagery and meteorological data. This transition from reactive to predictive monitoring is essential for proactive urban sustainability planning and resource allocation.

Satellite imagery integrated with AI and ground-based sensor data enables automated mapping of urban green spaces and vegetation distribution. Advanced semantic segmentation architectures like improved DeepLabV3+ enhance vegetation detection accuracy compared to traditional spectral indices, supporting equitable green-space planning that prioritizes areas experiencing greatest heat stress and air pollution exposure.[13][14]

5- Safety and Surveillance Enhancement

AI-powered surveillance systems enhance urban safety by actively monitoring public spaces and detecting threats in real time. Leveraging computer vision and deep learning, these systems identify anomalies such as unattended objects, abnormal crowd behavior, vandalism, and security breaches, enabling faster emergency responses than traditional passive CCTV systems. By automating threat detection, AI reduces reliance on manual monitoring, which is prone to fatigue and inefficiency, and triggers immediate alerts to security personnel when suspicious behavior or intrusions are detected.

Stockholm's deployment of AI-enabled CCTV in subway networks illustrates the impact of such systems, achieving a 25% reduction in crimes like pickpocketing and robbery. Real-time monitoring allows authorities to respond swiftly to unauthorized access or dubious actions, improving public safety outcomes.

Despite these advantages, AI-driven surveillance raises important concerns around privacy, data governance, and civil liberties. Ensuring responsible use requires transparent deployment, strict data protection measures, and strong oversight to maintain public trust. [15][16]

6- Tourism and Entertainment Services

Personalized Travel Planning and Recommendation Systems. AI is transforming tourism services by enabling highly personalized travel planning and recommendation systems. By analyzing user data such as preferences, browsing behavior, and past interactions, AI algorithms generate tailored suggestions for destinations, accommodations, dining, and activities. These systems improve user experience, reduce planning effort, and increase booking rates, while supporting both consumer-facing and business-to-business tourism platforms.

AI-driven demand forecasting for tourism flows analyzes historical visitation data, seasonal patterns, weather influences, and event schedules to predict visitor surges, enabling services to adjust staffing, attraction capacity, and transportation dynamically. This capability reduces over-tourism impacts in sensitive cultural and environmental areas while maintaining economic viability. [17][18]

7- Smart Buildings and Building Automation

AI-driven HVAC optimization represents one of the highest-impact applications for building energy efficiency and occupant comfort. AI-integrated Building Management Systems (BMS) leverage data from smart sensors and IoT devices that capture real-time information on temperature, humidity, occupancy, motion, air quality, and energy use. Unlike traditional automation relying on preset rules, AI analyses sensor data to recognize usage patterns, forecast future needs, and make informed decisions autonomously. Adaptive HVAC control adjusts heating and cooling dynamically based on weather forecasts, occupancy patterns, thermal zoning, and historical consumption data.

A commercial office tower in Singapore implementing an AI-powered BMS achieved a 22% reduction in energy costs over 12 months, improved tenant satisfaction scores, and detected over 150 maintenance issues before they escalated into failures. [19]

Smart systems adjust lighting, temperature, and air quality in real-time to match occupant preferences and numbers, creating personalized comfort experiences. AI tracks occupancy patterns to suggest better usage of meeting rooms, workspaces, and public areas, optimizing space allocation and reducing wasted resources. During emergencies, AI directs occupants safely using digital signage, alerts, and access controls, enhancing building safety.

8- Energy Management

Microgrids—small, localized energy systems capable of operating independently from the larger grid—provide communities with resilience, control, and the ability to integrate renewable energy sources such as rooftop solar panels and wind turbines. AI improves energy reliability by integrating data about energy consumption, electricity market prices, weather forecasts, and renewable energy availability—critical when using weather-dependent wind and solar power.

Advanced AI forecasting predicts renewable energy generation, while AI-driven analytics determine optimal times to generate, store, or sell electricity. Machine learning algorithms analyze real-time data to balance supply and demand dynamically, increasing efficiency and stabilizing the grid. Deep learning-based energy management systems optimize battery state-of-charge (SOC), ensuring energy storage is used efficiently to meet community needs while maximizing cost savings.

Predictive maintenance systems apply pattern recognition to grid sensor data to detect faults in transformers, distribution lines, and generation facilities early, preventing cascading failures and extending critical infrastructure lifespan. [20]

9- Citizen Service and Smart Governance

AI can significantly enhance municipal efficiency by automating routine tasks and optimizing internal workflows, which reduces administrative burden and improves the speed and reliability of public services. When repetitive, low-value work is handled by AI, municipal staff can shift time toward strategic planning, complex case management, and higher-impact public-facing responsibilities, often improving overall citizen engagement because residents receive faster answers and clearer service pathways.

AI tools can be deployed along a spectrum of complexity, and many high-value applications do not require advanced or expensive systems. Cities can start with simpler solutions, such as chatbots, automated document handling, or service-request routing, to build experience, data practices, and institutional capacity before moving to more sophisticated analytics like predictive modelling or resource optimization. This stepwise approach lowers risk while still delivering early efficiency gains.

In citizen-facing services, AI frequently improves access to information and reduces pressure on call centers by answering common questions, triggering requests, and guiding residents to the right department. Examples include chatbot deployments in Bogotá (Colombia) and Buenos Aires (Argentina) to provide faster, more accessible communication with residents. In Matosinhos (Portugal), the municipality launched

"Maria" in 2024, a multilingual AI assistant available 24/7 via chat, voice, and web channels; it handles routine inquiries on municipal services, tourism, and family programmers, while routing complex or sensitive cases to human staff (Municipality of Matosinhos, 2024). This kind of system can also support continuity of essential information during disruptions or crises by keeping service channels responsive at all hours.

Beyond front-office interactions, AI is increasingly integrated into back-office operations such as finance, human resources, and regulatory management. Typical uses include automated document classification and paperwork processing, automated scheduling and routing (e.g., inspections, street cleaning, waste collection), and basic predictive analytics to anticipate demand or maintenance needs. In Virginia (United States), the Office of Regulatory Management has reduced more than a quarter of existing regulations and is deploying agentic AI to accelerate regulatory review and simplification, with projected annual savings of over USD 1.2 billion. [21]

Overall, municipal AI initiatives can improve both internal administrative performance and the quality of services delivered to residents.

1.2. AI Integration with Other Smart City Technologies

Smart cities represent one of the most consequential applications of converged technology in urban environments. These intelligent ecosystems leverage interconnected **IoT, cloud computing infrastructure, big data, 5G network, digital twins**, and artificial intelligence to optimize municipal operations across transportation, energy, public safety, and environmental management. AI's transformative power is amplified when integrated with complementary technologies, creating synergistic capabilities that exceed the sum of individual parts. This section explores how AI interacts with mentioned technologies, to enable intelligent urban ecosystems.

This section provides a brief explanation of each key technology before analyzing their integrated role in smart city structures.

The Internet of Things (IoT) describes the network of physical objects "things" that are embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices and systems over the internet. IoT sensing devices, such as loop detectors, proximity and infrared sensors, chemical and biosensors, and smart meters, form a crucial part of smart city infrastructure.

Big data refers to extremely large and complex data sets that are too big and fast-changing for traditional software or databases to store, process, and analyze efficiently. Big data works by collecting huge amounts of data from many sources, storing it in distributed systems, and processing it in parallel to extracting patterns, trends, and insights for decision-making.

Cloud computing is the delivery of computing services (like servers, storage, databases, networking, and software) over the internet, so users can access resources on demand and pay only for what they use. In smart city structures, cloud computing provides scalable storage, real-time processing, and analytics for massive IoT data from sensors, traffic systems, and utilities, enabling efficient urban management like optimized traffic and energy use.

Digital twins are virtual replicas of physical objects, systems, or entire cities that use real-time data from sensors and IoT to mirror, simulate, and optimize real-world operations.

5G connectivity provides ultra-fast speeds, low latency, and massive device connectivity essential for smart cities, powering real-time IoT data transmission for traffic management, surveillance, autonomous vehicles, and efficient urban networks. [22]

In the following there is a 6 layered structure to show the architecture of the smart city from data flow perspective and how this technology works togethers. [23]

application	Security, energy, waste management, governance, transportation, agriculture, etc.
learning techniques	Artificial Intelligence, Machine Learning, Fuzzy Logic, Data mining, etc
computing	Cloud Computing, Edge Computing, Fog Computing, Grid Computing, etc..
Communication	Wireless Sensor Network, 4G/5G, Wi-Fi, Wireless Access in Vehicular Environment, etc.
Data management	Big data, Hadoop, relational and NoSQL databases
sensors	Loop detectors, cameras, proximity, infrared, chemical and bio sensors, etc.

Figure 4: Schematic of various levels of smart city components implementation, and technology used

1. Sensors Layer

This is the foundation of a smart city ecosystem. It consists of all devices that directly interact with the environment.

- **Technologies involved:**

IoT (Internet of Things) sensors such as loop detectors (for vehicle counts), cameras (for surveillance and traffic analysis), proximity and infrared sensors (for motion and presence detection), chemical and biosensors (for air or water quality), and smart meters (for utilities like water, gas, electricity).

- **Role explained:**

Sensors collect raw observational data about everything happening in the city, from the flow of traffic and levels of pollution to noise levels, energy consumption, and security incidents. This raw data becomes the input foundation for all higher layers that analyze, store, and make sense of it. For instance, traffic cameras feed data to systems that control lights dynamically based on road congestion.

- **AI integration:**

AI can already assist at this level, often using edge AI, meaning lightweight processing happens directly on or near the sensor, before sending large data streams to the cloud. Examples:

- Detecting impossible or faulty readings automatically
- Recognizing patterns like motion, presence, or vehicle type in video data so only relevant summaries are transmitted. This reduces network load, improves responsiveness, and ensures system robustness.

2. Data Management Layer

This layer handles everything related to data storage, organization, and accessibility.

- **Technologies involved:**

Big data frameworks such as Hadoop, Spark, and relational databases (like SQL) systems.

- **Role explained:**

Massive streams of city data — coming from sensors, social media, camera, weather APIs, and infrastructure systems — are too complex to manage manually. This layer ensures data is properly indexed, searchable, and accessible both historically and in real time. For example, a traffic management system can analyze past traffic jams and current congestion simultaneously.

- **AI integration with Big Data:**

AI relies on this layer for both training and real-time inference. Historical data allows training models that forecast traffic or energy use, while live data updates those predictions in real time. In return, AI helps maintain data quality by spotting inconsistent records, identifying outliers, matching schemas across systems, and ensuring that all references to the same entity (like a road or power grid component) are linked.

- **Digital Twin connection:**

A digital twin—a virtual model of the physical city—requires accurate real-time and historical data. This layer ensures the twin remains synchronized with reality by feeding it live updates and calibration data.

3. Communication Layer

This layer connects all the physical and digital parts of the city through network infrastructure.

- **Technologies involved:**

Wireless Sensor Networks (WSNs), 4G/5G, Wi-Fi, etc.

- **Role explained:**

Its main role is to move data between components:

- From sensors in the field to data centers or cloud storage.
- From centralized control systems back to street-level actuators (like traffic lights or public displays).

- **AI integration:**

AI algorithms can manage network efficiency automatically by predicting traffic surges, dynamically rerouting packets, allocating network resources, and identifying possible intrusions or anomalies. For instance, AI may prioritize data streams for emergency vehicles or security systems over less critical background data.

4. Computing Layer

This layer supplies the computing power needed to process, analyze, and simulate all gathered data.

- **Technologies involved:**

Cloud computing (data centers providing scalable resources), edge computing (computation near data sources).

- **Role explained:**

This layer balances where computation occurs:

  - Edge: Handle quick, local reactions to data near where it's generated (for instance, adjusting streetlight when pedestrians are detected).
  - Cloud: Handles heavier workloads — long-term analytics, storage, training complex models, and managing digital twins.

- **AI integration:**

In the cloud, AI models are trained using massive data sets to predict large-scale behaviors (predicting citywide power demand or optimizing multi-modal transportation).

At the edge, smaller AI models perform time-sensitive tasks (detecting accidents from video feeds or optimizing traffic light timing live).

- **Digital Twin connection:**

Digital twins often live in the cloud or in a hybrid setup, using distributed computing to simulate different city scenarios (like flood risk or traffic diversions) and share insights with many city departments at once.

5. Learning Techniques Layer

This is the intelligence part of the system, where insights, predictions, and decisions are produced.

- **Technologies involved:**

AI, Machine Learning (ML), Deep Learning, and Data Mining methods.

- **Role explained:**

This layer transforms raw data into actionable knowledge, predicting trends, classifying events, and recommending optimal actions. It reinforces smart city capabilities like energy optimization, predictive maintenance, and adaptive control systems. [24][25][26][27]

1.2.1. Challenges of AI Adaptation in Urban Contexts

Despite the transformative potential of artificial intelligence (AI) in enhancing smart city services, such as transportation, healthcare, governance, and sustainability, its adoption remains uneven and often limited. This inconsistency is not primarily due to technological immaturity, but rather to a complex set of interrelated barriers that hinder effective implementation. AI adoption in smart cities is a socio-technical process: algorithms do not operate in a vacuum, but within institutional structures, regulatory environments, and social contexts that can either enable or constrain their use.

The literature highlights that AI adoption challenges extend beyond technical feasibility and include organizational readiness, environmental conditions, ethical concerns, and public acceptance. Issues such as privacy risks, cybersecurity threats, lack of transparency in AI decision-making, financial constraints, skill shortages, and societal fears about job displacement frequently emerge as critical obstacles. These barriers interact with one another, meaning that failure to address one dimension, such as governance or trust, can undermine progress in others.

To systematically capture these challenges, *"Barriers to artificial intelligence adoption in smart cities- Ben Rjab et al. (2023)"* research has organized AI adoption barriers in smart cities using the Technology–Organization–Environment (TOE) framework. This approach allows for a holistic understanding of how internal capabilities, technological characteristics, and external societal factors jointly influence adoption outcomes. The following table presents a structured overview of the key barriers identified in the literature, categorized by TOE dimensions and briefly explained to support analytical clarity. [28]

Table 1: Key barriers based on TOE dimensions

TOE CATEGORY	BARRIER	DESCRIPTION
TECHNOLOGICAL	Privacy issues	Concerns related to the collection, processing, and sharing of citizens' personal data through AI-enabled sensors, surveillance systems, and smart services, often without explicit consent.
	Cybersecurity issues	Vulnerability of AI systems and interconnected smart city infrastructures to cyberattacks, data manipulation, and system intrusion.
	Lack of AI explainability	Difficulty in understanding, interpreting, and justifying AI-driven decisions due to the "black-box" nature of many algorithms, reducing transparency and accountability.
	Decision-making issues	Risks of biased, incorrect, or unaccountable decisions made or supported by AI systems in critical urban services.
	Complexity of AI implementation	Technical and operational difficulty in designing, deploying, integrating, and maintaining AI systems within complex urban environments.
	Data quality and availability	Insufficient, biased, fragmented, or low-quality data required to train and operate AI models effectively.
	Disruptive nature of AI	The capacity of AI to radically alter existing processes, governance structures, and service models, creating uncertainty and resistance.
	Digital divide	Risk that AI adoption disproportionately benefits digitally literate or affluent populations, exacerbating social and economic inequalities.
	Singularity and ethical concerns	Fears related to loss of human control, ethical misuse, or long-term existential risks associated with advanced AI systems.
ORGANIZATIONAL	Lack of financial resources	High costs of AI acquisition, infrastructure development, maintenance, and experimentation, limiting investment capacity.
	Lack of IT infrastructure	Inadequate digital infrastructure (e.g., computing power, networks, cloud services) to support AI deployment.
	Limited human skills	Shortage of qualified personnel with

		expertise in AI development, data science, and system management within city administrations.
	Employee resistance to change	Organizational inertia and resistance from employees and managers who perceive AI as a threat to roles, routines, or authority.
ENVIRONMENTAL	Mass unemployment concerns	Fear that automation enabled by AI will replace human labor, leading to job losses and social instability.
	Public fear and lack of trust	Low public acceptance driven by fear, misinformation, ethical concerns, and lack of confidence in AI-driven systems.
	Legal and regulatory uncertainty	Absence or ambiguity of laws, standards, and accountability frameworks governing AI use in urban contexts.
	Ethical and social concerns	Broader societal debates about fairness, surveillance, discrimination, and human rights in AI-enabled cities.

1.3. The Smart City

Smart cities represent a transformative approach to urban development, leveraging advanced technologies, data-driven governance, and citizen-centric design to enhance efficiency, sustainability, and quality of life for residents. This section provides foundational context by first defining the smart city concept and tracing its historical evolution from early conceptualizations in the 1960s to widespread global implementations today. It then delineates the core domains of smart cities, such as mobility, energy, governance, and built environments, laying the groundwork for deeper analysis of real-world projects. [29][31]

1.3.1. Definition and evolution

From Urban Computing to Human-Centric Models

The concept of the smart city did not emerge suddenly with recent advances in digital technology. Instead, it represents the outcome of a long historical process in which cities progressively integrated computation, data, and communication technologies into urban planning and management. Understanding this evolution is essential for explaining why smart city definitions remain diverse and contested today. [29][30]

Early Urban Computing and Data-Driven Planning (1960s–1980s)

The earliest foundations of smart cities can be traced back to the first applications of computers in urban analysis during the late 1960s and 1970s. At this stage, cities were not described as "smart," but they began experimenting with computational tools to better understand and manage complex urban systems. A frequently cited milestone is the work of the Los Angeles Community Analysis Bureau, which in 1974 produced *A Cluster Analysis of Los Angeles*. This project applied statistical computing techniques to large urban datasets and is often regarded as one of the earliest examples of "urban big data." [29][51]

Throughout the 1980s, information and communication technologies (ICT) became increasingly embedded in municipal operations. Traffic control systems, utility management, and administrative databases started to rely on computerized processes, improving efficiency and coordination. While these initiatives were largely technical and operational, they introduced two ideas that later became central to smart city thinking: data-driven analysis of urban conditions and computer-assisted management of city services. These developments laid the groundwork for more integrated and networked urban systems in subsequent decades. [29][53]

From Digital and Intelligent Cities to Smart Cities (1990s)

The 1990s marked a conceptual transition as the spread of the internet transformed how cities thought about connectivity, information, and public services. During this period, terms such as "digital city" and "intelligent city" gained prominence. One of the most influential early experiments was Amsterdam's *De Digitale Stad* (The Digital City), launched in 1994. Designed as a virtual city, it aimed to promote internet literacy and create online public spaces for civic interaction. Although limited by the technologies of its time, it demonstrated how digital platforms could support urban communities and participation. [29][52]

At the same time, academic literature began to describe "intelligent cities" as urban areas that combine ICT infrastructure with knowledge institutions, innovation ecosystems, and human capital. Scholars such as Komninos note that the term "smart city" itself appeared sporadically in the late 1980s and early 1990s, mainly in relation to mobility systems and IT-enabled services. However, its usage remained fragmented and lacked a unified conceptual framework. During this phase, the dominant emphasis was on connectivity, e-government, broadband networks, and cities' roles as nodes within emerging digital and knowledge networks. [30]

Corporate-Led and Infrastructure-Centric Phase (Mid-2000s)

The mid-2000s represent a major turning point in the global diffusion of the smart city concept. Large ICT corporations played a decisive role in shaping both the language and the practical implementation of smart city initiatives. In 2005, Cisco announced significant investments in smart city research, followed by IBM's influential "Smarter Planet" campaign in 2008. IBM's subsequent "Smarter Cities" initiative in 2009 further institutionalized the concept by promoting integrated urban operations centers and data-driven management systems.[29][54]

This period is often described as the symbolic "birth" of the modern smart city agenda. Projects focused heavily on infrastructure efficiency, including smart grids, intelligent transportation systems, sensor networks, and centralized control rooms.

Expansion, Policy Mainstreaming, and Citizen Focus (2010s)

During the 2010s, smart city initiatives expanded rapidly across regions and policy levels. National and regional governments launched large-scale programs such as smart grid initiatives in Europe and the United States, Japan's designation of Yokohama as a smart city demonstrator, and China's extensive rollout of smart city pilot projects. At the city level, places such as Barcelona, Amsterdam, Singapore, Copenhagen, and Dubai became global reference points through integrated projects in transport, energy, lighting, and urban services.

This decade also marked the mainstreaming of smart cities as a global policy agenda, symbolized by the launch of the Smart City Expo World Congress in Barcelona in 2011. Importantly, the focus of smart city discourse began to shift. While infrastructure and efficiency remained important, greater attention was given to sustainability, quality of life, and governance. Open data initiatives, digital participation platforms, and civic innovation ecosystems became central elements. At the same time, smart city strategies are increasingly aligned with climate policy, energy transition, and low-carbon development goals.[29][31][54]

Social and ethical concerns also gained importance. Issues such as digital divides, privacy, surveillance, and data ownership prompted calls for more inclusive and rights-based smart city models. By the end of the 2010s, the smart city was no longer viewed merely as a technological system, but as a broader urban strategy integrating technology, governance reform, sustainability, and citizen engagement.

Recent Trends and the 2020s

In the 2020s, smart city research and practice emphasize integration, resilience, and ethical governance. Advances in the Internet of Things, big data analytics, artificial intelligence, and 5G have enabled real-time monitoring and predictive management of urban systems, including traffic optimization, energy demand response, and predictive maintenance. At the same time, cities increasingly seek to integrate multiple domains—transport, energy, health, education, and governance—into unified digital platforms and digital twins. [29][30][55]

Recent global crises, particularly the COVID-19 pandemic and climate-related disasters, have highlighted the role of smart city infrastructures in resilience, public health surveillance, and emergency response. However, these developments have also intensified concerns about surveillance, algorithmic bias, and unequal access to technology. As a result, contemporary smart city discourse places strong emphasis on ethical frameworks, human-centered design, and democratic governance.[31][55][56]

Generations and Models of Smart Cities

To make sense of this evolution, many authors describe successive generations of smart cities.

Smart City 1.0 refers to the technology-driven, vendor-led phase focused on infrastructure efficiency.

Smart City 2.0 reflects a shift toward government-led strategies aligned with broader policy objectives.

Smart City 3.0 emphasizes citizen-centric and co-created solutions, involving residents, startups, and civil society.

Smart City 4.0 highlights data-intensive and AI-enabled systems with deep cross-domain integration.

Emerging discussions of Smart City 5.0 align smart city development with human wellbeing, social inclusion, and planetary sustainability, explicitly subordinating technology to social and environmental goals.[57]

1.3.2. Application Fields

A smart city encompasses multiple application domains in which technology is leveraged to meaningfully improve urban living conditions. Based on a synthesis of academic literature and the analytical framework developed by the Smart City Observatory of the Polytechnic of Milan, nine key dimensions have been identified. This structured approach provides a comprehensive and coherent view of the smart city concept.

1.3.2.1. Smart Mobility

Smart mobility in smart cities is a comprehensive socio-technical concept that responds to persistent urban problems such as congestion, air pollution, noise, road accidents, and the high operating costs of traditional transport systems. The central idea is to deliver high-quality mobility services to citizens, fast, reliable, affordable, inclusive, while at the same time reducing environmental impacts and dependence on private car ownership. To achieve this, smart mobility combines multiple modes of transport (public transit, walking, cycling, micro-mobility, car-sharing, ride-hailing, logistics) into an integrated system that is planned and operated based on real-time data, predictive analytics, and seamless digital services.

A key paradigm in this field is **Mobility-as-a-Service (MaaS)**, which shifts the focus from owning a vehicle to accessing mobility as an on-demand service through digital platforms. MaaS platforms **integrate public transport, ride-sharing, bike-sharing, car-sharing, taxis** and sometimes long-distance services into a single interface that offers journey planning, booking, ticketing and payment, usually through one account and one app. This integration enables advanced services such as door-to-door multimodal journeys, where a user can, for example, combine bike-sharing, metro and walking in a single, optimized itinerary without needing to switch between multiple apps or ticketing systems. In such systems, dynamic pricing and personalized suggestions can nudge travelers toward more sustainable choices (e.g., public transport plus walking) and away from peak-hour car trips, supporting both operational efficiency and climate goals.

At the technical level, smart mobility relies on a stack of enabling technologies: Internet-of-Things (IoT) sensors embedded in roads, vehicles, traffic signals and parking infrastructure; Global Positioning System (GPS) units in vehicles and smartphones; advanced communication networks such as 4G/5G; and back-end platforms that aggregate and analyze data at scale. Sensors and connectivity provide continuous streams of information on traffic volumes, speeds, occupancy of buses and trains, parking availability, vehicle status, and environmental conditions, forming the raw material for data-driven decision-making. Artificial intelligence and big data analytics then process these datasets to recognize patterns, predict congestion, estimate travel times, and recommend optimal routes or service adjustments, turning data into operational intelligence. This enables vehicles to interact with each other (V2V) and with city infrastructure (V2I), supporting cooperative driving, safer intersections, traffic signals, and coordinated priority for public transport or emergency vehicles at junctions.

Intelligent Transport Systems (ITS) play a crucial role as the operational layer that applies this intelligence to real-world control of networks. ITS integrates traffic management centers, signal control systems, public transport control, traveler information services, and sometimes merchandise/logistics management into a coherent framework. Data from GPS, sensors, cameras and vehicles is continuously fed into ITS platforms, where algorithms (increasingly AI-based) are used to detect incidents, monitor congestion, and optimize both traffic signals and public transport operations in real time. For road users, this translates into traveler information services—apps, variable message signs, in-vehicle navigation—that provide early warnings about accidents, congestion, roadworks or weather conditions, and suggest alternative routes or modes. For operators, ITS supports dynamic lane management, ramp metering, adaptive signal control, and coordinated priority for buses and trams, all aimed at reducing travel times, emissions, and accident risks while making better use of existing infrastructure.

Smart mobility also encompasses a broad field of concrete applications at street level. These include roads equipped with sensors monitoring traffic and pavement conditions; adaptive traffic lights that adjust cycle times based on measured flows and give priority to pedestrians, cyclists or public transport at key times; micro-mobility services (shared bikes and e-scooters) that provide first- and last-mile connectivity; car-sharing and ride-pooling services that reduce the need for private car ownership; and green transportation initiatives such as extensive cycling networks and electrified bus fleets. Additional examples are automated toll collection systems that reduce delays at toll plazas; smart parking systems that guide drivers to available spaces and support dynamic pricing; integrated ticketing where one account or card can be used across buses, metro, bike share and car share; and mobility hubs that physically co-locate different modes so that transfers are simple and intuitive. The combined effect of these measures, when governed and integrated properly, is a mobility ecosystem that is more flexible, efficient, clean and safe, supporting social inclusion and economic productivity while responding adaptively to evolving urban conditions. [32][33][34]

Amsterdam – Proactive Traffic Management and Code the Streets

Amsterdam's approach demonstrates smart mobility in action. The city partners with navigation providers like TomTom to share real-time traffic data, enabling predictive congestion management. The "Code the Streets" initiative coordinates data between city systems and private mobility apps to suggest "social routes" that avoid schools, reduce pollution, or ease congestion, integrating ITS with MaaS principles for city-wide benefits. Code the Streets started as an EIT Urban Mobility project in **2021**, with initial **pilots** completed in Amsterdam and Helsinki, and that it is still active in a development/scale-up phase, producing tools, APIs and guidance for wider city deployment. [35]

1.3.2.2. Smart Lighting

Urban lighting consumes a large share of municipal energy budgets, often running at fixed intensities regardless of need, leading to waste, light pollution, and high costs. Smart lighting addresses this by deploying connected LED systems that dynamically adjust brightness based on time, weather, traffic, and occupancy, while enabling remote monitoring and multi-use infrastructure. The core concept is to provide optimal illumination for safety and visibility exactly where and when required, simultaneously cutting energy use, reducing CO_2 emissions, and minimizing maintenance through predictive fault detection. This shift from static to adaptive lighting transforms streetlights into intelligent nodes that can host sensors for air quality, noise, traffic detection, and even 5G small cells, creating a foundational digital infrastructure layer for broader smart city applications.

Key technologies encompass LED luminaires with dimmable drivers, wireless mesh networks for communication, photocells for ambient light sensing, motion/occupancy detectors (radar or camera-based), and centralized control platforms with analytics dashboards. These enable lighting profiles tailored to zone types (brighter on pedestrian paths at night, dimmer in residential areas during low activity), automatic fault reporting (vandalism, bulb failure), and integration with other city systems (brighter lights during detected incidents). The significant role of context-aware algorithms cannot be overlooked: they process inputs from multiple sources to balance energy savings with safety, for instance increasing illumination when cyclists or pedestrians are detected or during fog or rain. [36][37][38]

Polish energy group turns to AI to manage street lighting

The Cartagena-EPM smart lighting **pilot** started in April **2025** with Phase 1, deploying 600 AI-enabled LED nodes for smart lighting where connected LED streetlights dynamically adjust brightness based on real-time occupancy, traffic, weather, and pedestrian activity via motion sensors, radar, and ambient light detectors. These systems host multi-use sensors for air quality (e.g., PM2.5, NO_2, ozone), noise, and mobility monitoring, enabling predictive fault detection, remote management, and up to 80% energy savings by dimming in low-activity zones like residential areas while boosting illumination during fog, rain, or incidents. Integrated with centralized AI platforms, the lights form intelligent nodes supporting broader smart city functions like 5G and environmental alerts, directly mirroring the described shift to adaptive, context-aware illumination that cuts CO_2 emissions and light pollution. [39]

1.3.2.3. Smart Waste Management

Overflowing bins, inefficient collection routes, illegal dumping, and high fuel/labor costs plague urban waste services, especially in commercial districts. Smart waste management revolutionizes this by using IoT sensors for real-time bin monitoring and analytics for demand-driven operations, ensuring cleanliness while minimizing unnecessary collections. The goal is high service quality (no overflows, fewer complaints) at lower cost and emissions, often achieving 60–80% reductions in overflow incidents through data optimization.

Technologies include ultrasonic level sensors (measuring multiple points per bin), temperature probes (fire prevention), GPS fleet tracking, route optimization algorithms, and dashboards predicting waste patterns by location, day, weather, and events. In pneumatic systems (for new districts), vacuum tubes transport waste underground to central facilities, eliminating street trucks.

San Francisco – Nordsense Sensor Pilot

San Francisco piloted Nordsense IoT sensors in 48 public trash cans in **2019** through the Startup in Residence program, achieving 80% less overflow, 66% fewer cleaning requests, and 64% reduced illegal dumping. The city then expanded to +1,000 sensors by 2023 across high-traffic areas like Chinatown and Downtown, enabling real-time fill-level monitoring, AI route optimization, and proactive collections. The system is fully **operational in 2026** as part of the city's Sustainable Plan, delivering cleaner streets and cost savings. [40]

1.3.2.4. Smart Environmental Monitoring

Urban environments face growing challenges from air pollution, urban heat islands, noise exposure, water quality degradation, biodiversity loss, and inefficient land use, all

exacerbated by climate change and densification. Traditional monitoring relies on sparse fixed stations with infrequent measurements, limiting actionable insights; smart environmental and land monitoring addresses this through dense, real-time sensor networks, geospatial analytics, and digital twins that provide granular data for proactive management. The core objective is to deliver high-quality environmental intelligence to citizens, planners, and policymakers, enabling pollution heat maps, health alerts, green space optimization, and climate adaptation, while reducing ecological footprints and supporting sustainable land allocation. This domain integrates environmental sensing with land management tools like GIS and 3D city models to link "what's happening" (real-time conditions) with "what to do" (zoning, greening, retrofits), turning data into regulatory enforcement, urban planning, and public engagement.
Key technologies include IoT sensors for air quality, meteorology (temperature, humidity, wind), noise, water levels/quality, and soil moisture; distributed on lampposts, buildings, vehicles, and drones for hyper-local coverage. Satellite/drone imagery and LiDAR provide land cover analysis; GIS platforms aggregate data into dashboards, heat maps, and predictive models (pollution forecasting via AI); 3D city models visualize impacts on buildings/facades (solar potential, flood risk). Open data portals enable citizen apps, research, and business innovation, while edge computing ensures low latency for alerts. Furthermore, the significant role of integrated platforms cannot be overlooked: they fuse sensor streams with satellite data and models to support applications like deforestation tracking, disaster response, and urban forestry management, achieving finer granularity than legacy methods. Examples include bike lane usage sensors promoting sustainable transport, weather stations for road safety alerts, and GIS for green space/tree inventories linking to land cadasters. [41]

Hong Kong – Smart Lampposts with Multi-Sensor Arrays
Hong Kong's Smart Lamppost Scheme deploys IoT-enabled poles in Kowloon East, equipped with air quality sensors (PM2.5, NO, NO_2), meteorological sensors (temperature, humidity), thermal detectors for traffic flow, and LiDAR for occupancy. Data streams to cloud platforms for district-level heat maps and analysis, powering sustainability decisions and public dashboards; Sapiens NAS sensors deployed **in 2018 PoC** across 15 sites provided real-time pollutants data, paving expansion while addressing privacy via anonymization. [42]

1.3.2.5. Smart Building

Smart buildings deliver significant advantages through IoT sensors and AI-driven analytics that enable real-time data collection, automation, and predictive optimization. These technologies work together: IoT devices monitor environmental factors like occupancy, temperature, energy use, and air quality, while AI processes this data to make intelligent decisions, such as adjusting HVAC systems or lighting dynamically.

Key benefits include optimized energy usage and cost savings, where sensors detect unoccupied areas to cut power automatically, reducing emissions by up to 28% of operational carbon footprints and lowering bills through targeted resource allocation. Predictive maintenance uses continuous IoT monitoring to spot faults early, AI algorithms analyze patterns to forecast issues like equipment wear, preventing costly breakdowns and enhancing safety, as seen in real-time alerts for structural weaknesses.

Further gains come from enhanced occupant comfort, productivity, and space utilization;

AI integrates data from IoT for personalized environments, like weather-responsive climate control and desk booking apps, boosting wellbeing and efficiency. Automation streamlines security with camera-linked sensors and rapid threat detection, while real-time insights inform broader decisions, increasing property value through proven sustainability and smart integrations.

The Edge, Amsterdam, Netherlands stands out as one of the world's most advanced smart buildings, earning a record-breaking 98.4% BREEAM sustainability rating—the highest ever from the British green building certification agency—for its pioneering integration of technology and eco-design. **Completed in 2014** by PLP Architecture for Deloitte, this 15-story, 40,000 m² office tower generates more energy than it consumes through solar panels on its roof and south facade, while employing nearly 28,000–30,000 IoT sensors to monitor occupancy, lighting, temperature, humidity, and energy use in real time. These sensors feed data into AI-powered dashboards that enable predictive maintenance (e.g., flagging bulb replacements or skipping cleaning in unused rooms), optimize resource allocation, and predict peak usage like lunch crowds using historical patterns, weather, and traffic data, slashing operational costs and emissions.

A standout feature is its custom smartphone app, which personalizes the occupant experience: upon arrival, it detects your vehicle via license plate recognition, guides you to an available parking spot, reserves a desk (as it's deskless), and adjusts your workspace's lighting, temperature, and even blinds to your stored preferences via "Light over Ethernet" (LoE), a PoE-powered LED system with 6,000 low-energy LEDs and embedded sensors for 20cm-precise indoor positioning and 50% lighting energy savings compared to standard systems. This IoT-AI synergy not only boosts productivity and wellbeing but integrates with rainwater harvesting, groundwater cooling, and heat-recovery ventilation for holistic efficiency, making The Edge a cornerstone of Amsterdam's smart city ecosystem. [44]

1.3.2.6. Safety and Surveillance

Crime, traffic accidents, medical emergencies, fires, and public disorder demand rapid detection, verification, and coordinated response in increasingly dense urban settings, where traditional patrols and calls are insufficient. Smart safety and surveillance systems integrate multi-source data (video, sensors, social media) with AI analytics and centralized command centers to enable proactive prevention, real-time alerts, and faster interventions, while addressing privacy concerns through governance frameworks like data minimization and human oversight. The key idea is to create a unified situational awareness layer that enhances public security without eroding trust, achieving outcomes like 20–50% faster response times and reduced incident severity through predictive capabilities. Technologies include high-resolution CCTV with intelligent video analytics (IVA) for anomaly detection (loitering, falls, crowds, weapons), ANPR for vehicle tracking/enforcement, acoustic sensors for gunshots/screams, drone integration for aerial views, and fusion platforms aggregating feeds into ops centers. AI processes streams for automated alerts (abandoned bags, traffic stalls), while governance ensures ethical use (audit logs, retention limits). Furthermore, integrated command centers orchestrate police, fire, EMS, and traffic teams via shared dashboards, turning siloed responses into coordinated actions.

Examples encompass facial recognition (with safeguards), predictive policing via crime pattern analysis, crowd management at events, and environmental criminology apps optimizing lighting/patrols. [45][46]

Singapore Protective Security Command – Strategic Location Response (SLR) In June **2025**, Singapore Police Force's ProCom **operationalized** SLR deployment, using advanced surveillance, real-time analytics, and command integration for high-risk sites, marked by a flag-off ceremony emphasizing frontline enhancement across the island. This builds on Safe City ops centers with IVA, denying unauthorized access and detecting threats proactively. [47]

1.3.2.7. Smart Tourism

Smart tourism represents the application of smart city principles to the tourism and vacation domain. It leverages digital technologies, data, and innovative service models to enhance visitor experiences while simultaneously managing tourism flows and protecting residents' quality of life. Rather than focusing solely on promotion, smart tourism aims to balance economic benefits with sustainability, livability, and effective destination management, addressing challenges such as overtourism, congestion, seasonal peaks, and uneven spatial distribution of visitors.

At its core, smart tourism integrates four interrelated layers. The first is the infrastructure and data layer, which includes digital connectivity (such as public Wi-Fi and mobile networks), sensing technologies (people counters, environmental sensors, mobility data), and diverse data sources ranging from booking platforms and transport systems to social media and open data portals. This layer connects tourism to the broader smart city ecosystem, particularly smart mobility and digital governance.

The second layer focuses on **services and visitor experience**. Smart tourism reshapes the entire visitor journey through digital tools such as destination apps, smart wayfinding, contactless ticketing, and immersive AR/VR content. These tools support personalization, real-time information, and adaptive recommendations based on location, preferences, and living conditions, thereby improving satisfaction and reducing friction during visits.

The third layer concerns destination management and operations, where smart tourism moves beyond apps toward systemic management. Real-time dashboards, predictive analytics, and demand-management tools allow authorities and destination management organizations to monitor visitor flows, forecast peaks, and actively redistribute demand through time-slot ticketing, dynamic pricing, and targeted communication. Operational decisions—such as staffing, cleaning, transport frequency, and security, can thus be aligned with actual demand rather than static plans.

The fourth layer addresses **governance**, **sustainability**, and **stakeholder** collaboration. Smart tourism emphasizes transparency through open data, the use of sustainability indicators that include environmental and social impacts, and participatory processes that involve residents and local businesses. Cross-sector integration ensures that tourism policies align with transport, housing, environmental, and cultural strategies, reinforcing a holistic approach to urban development.

Julia is Rome's generative AI virtual assistant, designed to enhance smart tourism by providing real-time, personalized guidance for visitors exploring the city. It supports tourists via WhatsApp, Telegram, web chat, and Messenger, offering certified info on events, museums, restaurants, public transport, cultural sites, Jubilee events, and practical services like fountains or pharmacies. **Announced October 23**, 2024, in collaboration with Microsoft/OpenAI, Julia launched its first release on March 7, 2025, ahead of Jubilee 2025. Version 2.0 rolled out July 30, 2025, with upgrades like GPT-4.1, better positioning, and new categories (e.g., shopping, sports).[58]

In summary, smart tourism can be understood as the strategic use of ICT—such as IoT, big data analytics, AI, mobile platforms, and AR/VR—to integrate physical, digital, and social dimensions of tourism. Its evolution reflects a broader shift in smart city thinking from technology-driven solutions toward data-informed, citizen-aware, and sustainability-oriented destination management.

1.3.2.8. Smart Metering & Grid

Smart metering and smart grids form the base of energy management in smart cities, enabling real-time monitoring, two-way communication, and dynamic optimization of electricity, gas, water, and heat flows. Smart meters replace traditional monthly manual readings with digital devices that record consumption and transmit data automatically to utilities via secure networks. Smart grids extend this intelligence across the entire network, integrating distributed energy resources (solar, wind, batteries) with demand-side management to balance supply and demand proactively.

How they work together: Smart meters create Advanced Metering Infrastructure (AMI), a system of meters, communication networks, data concentrators, and head-end servers. Meters act as gateways aggregating water/gas data via Wireless M-Bus, feeding into Meter Data Management Systems (MDMS) for billing, analytics, and alerts. Smart grids use this data plus grid sensors (voltage, faults) in control centres where AI predicts peaks, automates demand response (e.g., cycling AC during heatwaves), enables time-of-use pricing, and supports microgrids for resilience. For example, when solar peaks exceed demand, excess flows to batteries or EVs via vehicle-to-grid (V2G); utilities send price signals to shift laundry to off-peak hours.[48][49][50]

1.3.2.9. Smart Government

Smart government in the smart city context refers to the use of digital technologies, data, and innovative governance models to improve how public institutions operate and how they interact with citizens, businesses, and other stakeholders. It functions as the governance backbone of a smart city, ensuring that technology is used to create public value rather than simply digitizing existing bureaucracy.

A key feature of smart government is data-driven decision-making. By integrating real-time and administrative data from multiple sources—such as public services, urban sensors, and digital platforms, governments can better understand current conditions and respond more effectively. This shifts policymaking from reactive and intuition-based approaches to evidence-based planning, improving the accuracy and timeliness of decisions.

Smart government also enhances public service delivery. Digital platforms and one-stop portals simplify access to services such as permits, registrations, tax payments, and social support. This reduces administrative burden, shortens processing times, and lowers operational costs. Services have become more user-centric, with better coordination across departments and less duplication of data collection.

Transparency and accountability are central outcomes of smart government. Through open data initiatives and digital reporting tools, governments can make information on budgets, performance indicators, and policy outcomes publicly accessible. This visibility strengthens public trust, enables external scrutiny, and supports more responsible use of public resources. Another important dimension is citizen participation. Smart government expands engagement through digital channels that allow residents to report issues, contribute ideas, and take part in consultations. This two-way interaction helps governments identify local problems more quickly and design policies that better reflect community needs. Internally, smart government improves coordination across public agencies by breaking down institutional silos. Shared data platforms and interoperable systems allow different departments to collaborate more effectively, aligning policies in areas such as transport, energy, environment, and social services. This integrated approach leads to more coherent and sustainable urban development.

2. Objectives and Methodology

This chapter aims to explain the objectives of the thesis and the methodological flow used for its composition. It is organized into four main parts that reflect the core areas of the entire work. The first section is dedicated to the objectives and research questions that refer to the entire study. The second section provides an explanation of how the introductory chapter was conducted and the last two sections are focused on the detailed description of the central part of the thesis, the creation of a database containing smart city projects and the analysis methods.

2.1 Objectives

The main aim of this thesis is to explore the current state of the art in the role of artificial intelligence within smart cities around the world. To achieve this, the study establishes a clear and comprehensive understanding of the Smart City concept, including its definition and evolution, the main domains which are considered to focus and invest, and AI definition and methodologies across these areas. To support the analysis, a detailed Excel database was created on smart city initiatives across 3 years 2023-2025. This dataset allows for the extraction of meaningful insights into the distribution of AI applications over different domains, database characteristics are used, status of maturity, outcome classification analysis, and importance of different organizational level to lead these projects and transformation.

The thesis further examines how societal priorities shape the distribution of AI-enabled smart city investments across different urban domains, such as mobility, energy, governance, and public services. In addition, the analysis evaluates the benefits generated by smart city projects, assessing their impact across different application areas. In the next section, the analysis moves beyond descriptive analysis by addressing the socio-technical complexity of AI initiatives in smart cities. It introduces a qualitative framework that classifies projects based on integration complexity along two dimensions: the scope of smart city domains involved (narrow, moderate, broad) and the breadth of AI functional classes applied (lightweight, intensive). By combining these two axes into a matrix, 6 archetypes are defined to classify the projects.

In summary, the central research question guiding this thesis is:
"What is the current state of the art in the global deployment of artificial intelligence within smart city initiatives?"
To address this question in depth, the analysis presented in this thesis focuses on smart city projects and developments from 2023 to 2025, ensuring an up-to-date and contemporary view of global trends. In addition to the main research question, several sub-questions are formulated to examine specific aspects of the topic in greater detail.

RQ1: *"How is the geographical distribution of smart city projects in the world?"*
RQ2: *" Which types of organizations and governmental levels are most involved in enabling AI-based smart city projects?"*
RQ3: *"Which smart city domains receive the highest focus in AI-based projects?"*
RQ4: *"How are data distributed across smart city projects, and which AI methods are most frequently used?"*
RQ5: *" the outcome generated by smart city projects impact on which part of society?"*

For the Mixed-Methods Analysis section:
RQ6: *"How is the complexity of smart city projects defined?"*

2.2. Methodology

As outlined in the introduction section, the literature review aims to provide a conceptual foundation for the thesis by creating key themes related to smart cities and artificial intelligence. To develop the introductory framework, an exploratory review of both **scientific literature and authoritative online sources** was conducted. This included journal articles accessed through academic search engines, as well as reports and news obtained from reputable institutional and professional websites.
Search engines such as Scopus and Research Gate, academic papers were used. The keywords used were the following:

- "Smart City"
- "Smart City" AND "Literature Review"
- "Smart City" AND "Application fields"
- "Smart City" AND "Benefits" AND "Challenges"
- "Artificial Intelligence"
- "Artificial Intelligence" AND "Smart city"

In addition to academic articles, professional websites were accessed to identify real-world smart city projects. These websites provide up-to-date information on smart city projects, city infrastructure developments, and strategic plans aimed at supporting future-oriented, technology-enabled urban environments.

The next phase of the research process involved using a resource provided by the Polytechnic of Milan, namely its **Newsletter**. This consists of weekly emails that gather the most interesting news in the Smart City field, highlighting the most significant technological and market trends, what types of projects are in execution or starting up, and administrative orders and actions by government bodies. However, it should be noted that information in emails was about all types of projects, not only the AI ones.

For the qualitative analysis, two analytical dimensions were defined to classify projects according to their scope and complexity. This framework enables an assessment of the current landscape by positioning the collected initiatives within the identified archetypes. The two dimensions were formulated based on a conceptual interpretation of project complexity and ecosystem alignment, consistent with the definitions adopted in this research context. Within the dataset, two dedicated columns were defined to flag each project according to the two analytical dimensions, enabling the consistent assignment of initiatives to their corresponding positions within the analytical framework.

2.3. The database creation

The development of an Excel-based database containing relevant information for analyzing and answering research questions, which is the current state of smart city projects, represents the central component of this thesis. This section describes the methodology adopted for database construction, including its structure and indicators.

2.3.1. The structure

To identify the key elements required for structuring the database, the Smart City Observatory database developed by the Politecnico di Milano research team was used as a reference. The Excel database was designed by combining the categorization approach adopted in the AI Watch[2] reports with the standardization methodology used by the Politecnico di Milano research team. This integrated structure ensures a consistent and systematic format for collecting and reporting information across all projects.

In the following there is a description of the database structure, it's crucial to note that each row in the Excel sheet represents a single smart city project described through different information by the columns names. The columns of database include:

- **Name**: it represents the exact name of the project which is defined in online source
- **Website**: Official page of the project/technology
- **Source**: source of news which is found in online websites
- **Description**: it represents a summary of the project
- **Status JRC**: The research has categorized the implementation status of the cases based on JRC report:
  - **Planned**: focuses on conceptualization and approval. At this stage, there is no defined operational scale, and the risk level is low.
  - **In development**: it is centered on creating solutions or technologies. Activities are carried out on a research scale, and the associated risk level is moderate.
  - **Pilot**: involves testing and validation of the solution. This phase is conducted on a small-scale and in a controlled environment, with a moderate to high level of risk.
  - **Implemented**: represents full-scale operation across the entire organization. At this point, the solution is proven.
- **Status Polimi:** It is very difficult to know the actual status of the project with the public information available, so here it is tried to consider a standard classification by polimi research team:
  - **Operative** would mean that the infrastructure is already built and functioning used in everyday
  - **Announcement** reflects the stage where the organization has declared their

[2] AI Watch. European landscape on the use of Artificial Intelligence by the Public Sector

intentions and detailed the project's scope but has not yet completed the construction or launched the services, not yet operative.

- **Proof of Concept** (Poc) involves testing the feasibility of the project on a smaller scale.

- **Start year:** the start year of the project included AI application

❖ **Geographical information:**

- **Geographical extent**: Local, National, Regional, Multinational
- **Geographic coverage Country**: name of the country
- **Geographic coverage NUTS 2021**: NUTS code for EU countries
- **Continent name**: Asia, Africa, Australia, Europe, Oceania, South America, North America

- **Governmental level and functions**
  - **Responsible Organizations**: the name of the responsible organizations, it illustrates the various actors involved in the execution of the project, and this does not mean that they have to necessarily fund the project. Therefore, this column includes names of companies as well as governmental entities at all levels. This could range from local municipalities to regional, national and multinational entities, depending on the scope and scale of the project. Additionally, private companies, whether they are large corporations or small businesses, can also play crucial roles, particularly in providing expertise, resources, or financial backing.
  - **Responsible Organization Category**: it shows the main group behind a smart city project, such as government, company, university, or community organization. This helps explain how different groups work together, especially public-private partnerships common in smart cities:
    - Academic research
    - Central-Government
    - Consortium (collaboration between different sectors)
    - Private sector (when public sectors outsource the project to private sectors, usually technology provider)
    - Local Government
    - Regional Government
  - **Functions of Government (COFOG level I & II)**[3]: developed by *the United Nations Statistics Division* (UNSD), The Classification of Functions of Government (COFOG) is a comprehensive framework that provides a detailed classification of the functions, or socioeconomic objectives, that governments aim to achieve through various kinds of expenditure. Following classification illustrates, first-level COFOG splits expenditure data into ten "functional" groups or sub-sectors.

[3] OECD

Table 2: COFOG framework

Main Category	Sub-category	Main Category	Sub-category
General public services	01.1 Executive and legislative organs, financial and fiscal affairs, external affairs 01.2 Foreign economic aid 01.3 General services 01.4 Basic research 01.5 R&D General public services 01.6 General public services n.e.c. 01.7 Public debt transactions	**Housing and community amenities**	06.1 Housing development 06.2 Community development 06.3 Water supply 06.4 Street lighting 06.5 R&D Housing and community amenities
Defence	02.1 Military defence 02.2 Civil defence 02.3 Foreign military aid 02.4 R&D Defence 02.5 Defence n.e.c.	**Health**	07.1 Medical products, appliances and equipment 07.2 Outpatient services 07.3 Hospital services 07.4 Public health services 07.5 R&D Health
Public order and safety	03.1 Police services 03.2 Fire-protection services 03.3 Law courts 03.4 Prisons 03.5 R&D Public order and safety 03.6 Public order and safety n.e.c.	**Recreation, culture and religion**	08.1 Recreational and sporting services 08.2 Cultural services 08.3 Broadcasting and publishing services 08.4 Religious and other community services 08.5 R&D Recreation, culture and religion
Economic affairs	04.1 General economic, commercial and labour affairs 04.2 Agriculture, forestry, fishing and hunting 04.3 Fuel and energy 04.4 Mining, manufacturing and construction 04.5 Transport 04.6 Communication 04.7 Other industries 04.8 R&D Economic affairs	**Education**	09.1 Pre-primary and primary education 09.2 Secondary education 09.3 Post-secondary non-tertiary education 09.4 Tertiary education 09.5 Education not definable by level 09.6 Subsidiary services to education 09.7 R&D Education 09.8 Education n.e.c.
Environmental protection	05.1 Waste management 05.2 Waste water management 05.3 Pollution abatement 05.4 Protection of biodiversity and landscape 05.5 R&D Environmental protection 05.6 Environmental protection n.e.c.	**Social protection**	10.1 Sickness and disability 10.2 Old age 10.3 Survivors 10.4 Family and children 10.5 Unemployment 10.6 Housing 10.7 Social exclusion n.e.c. 10.8 R&D Social protection 10.9 Social protection n.e.c.

- **AI Taxonomy (AI classification):** In this classification, an effort was made to identify the practical applications of AI technologies based on their functions in a standardized manner, representing how AI is applied in each case. The following presents this classification:

Table 3: AI Taxonomy

AI Categories	Description
Generative Language, Conversation, and Translation Systems	Systems capable of generating textual outputs, performing actions, and/or providing services to a human user, based on commands and/or requests received through natural language interaction (written or spoken).
Generative Image, Video & Audio Systems	Systems capable of generating images, videos, or audio based on commands and requests from a human user.
Generative Design & Engineering Systems	Software systems that create and optimize 3D models for the design of artifacts, based on requirements and constraints specified by the user.
Text Analysis & Classification Systems	Solutions for analyzing and processing language, with purposes ranging from classification to understanding textual content.
Image & Video Analysis Systems	Solutions for analyzing images and videos focused on recognizing people, animals, and objects, biometric recognition, and extracting information from images and/or videos in general.
Audio (non-language) Analysis Systems	Extraction of information and content from audio signals for analysis, classification, storage, retrieval, or synthesis of audio files.
Data Exploration & Prediction Systems	Solutions that enable automated identification of potential patterns or regularities in available data or allow for predictions or forecasts of future variable behavior.
Recommendation Systems	Solutions aimed at providing users with suggestions (e.g., products to buy, training activities) based on information provided directly or indirectly by the user or through similarities with other users.
Decision Support & Optimization Systems	Solutions designed to support business decision-making and capable of modifying model variables to optimize an objective function (e.g., production optimization).
Process Orchestration Systems	Solutions that enable intelligent coordination of the various sections of a business process, simplifying and automating various activities.
Autonomous Driving	Autonomous vehicles capable of perceiving the external environment and determining the correct exercises to perform.
Intelligent Robots	Robots capable of moving themselves, or parts of themselves, manipulating objects, and performing various tasks without human intervention.
Intelligent Objects	Objects capable of executing actions and making decisions through data analysis, primarily (or exclusively) performed locally using AI algorithms (e.g., drones, AGVs, smart cameras).

- **Process types:** This classification[4] has been designed to answer the question "What activity does the AI technology support?" For this thesis, only the 4 main categories (process type) were utilized to prevent misclassification of individual projects:

Table 4: Process type Classification

Process type	Application type	Description
Analysis, monitoring and regulatory research	Information analysis processes	Information and data analysis is the process of inspecting, transforming, and modelling information. It is made by converting information into actionable knowledge (e.g. dashboard to support decision-making).
	Monitoring policy implementation	Processes that follow and assess implementation policies to ensure they are developed, endorsed, and implemented.
	Prediction and planning	Processes for management of resources based on prediction models, to support planning.
Enforcement	Smart recognition processes	Processes that can identify objects, people, places, texts, situations and actions in images, video, audio, or other detectable physical phenomena.
	Management of auditing and logging	Collection of records, and/or destination and source of records that provide documentary evidence of the sequence of activities that have affected at any time a specific operation, procedure, event, or device
	Predictive enforcement processes	Processes that analyze amounts of information available to predict and help prevent potential future crimes/mistakes/misunderstandings.
	Supporting inspection processes	Supporting processes used to identify wrongdoing or mistakes before an intervention by the responsible authorities (e.g. tax positions to be checked, businesses registered with anomalies).
Internal management	Internal primary processes	Processes directly create value for the external customer and the impact of their performance on the level of customer (citizens, firms) satisfaction.
	Internal support processes	Processes that produce services and information for the functioning of the organization. They have only internal customers
	Internal management processes	Processes that provide management, control and decision support tools necessary to achieve the organization's objectives and which have stakeholders and managers as clients
Public services and engagement	Engagement management	Establish and enhance connections with citizens and businesses to build trust at every point in their PS journey throughout the user relationship established
	Data Sharing Management	Data sharing processes support access to PS data, considering interoperability and data licensing (e.g. open data).
	Service integration	Service Integration is the management of the integration of multiple service suppliers and information sources to provide a tailored new specific service to citizens or other organizations or even for internal purposes
	Service personalization	Delivering customized services considering the needs of the customer (citizen/businesses/civil servant). Recommendation systems are here included.

[4] AI Watch. European landscape on the use of Artificial Intelligence by the Public Sector

- **Interactions**: The implementation of AI solutions implies interaction among different actors. The public sector is mainly involved in three types of relations:
  - **Government-to-Government (G2G).** Processes between and within public organizations, like services and information transactions between the central-state government, state-local governments, and between department-level and attached agencies.
  - **Government-to-Citizen (G2C)**. Services and information transactions by the government interacting with private users (citizens).
  - **Government-to-Business (G2B).** Services and information transactions by the government to private organizations.

- **Date Scope**: The data scope for this smart city governance project is categorized into three classes: dynamic data, historical data, and locational data:
  - **Dynamic Data:** Dynamic data refers to real-time or near-real-time information streams generated continuously from sensors, IoT devices, and live systems.
  - **Historical Data**: Historical data encompasses archived records and past datasets accumulated over time from operational systems and projects, and documents.
  - **Locational Data:** Locational data includes geospatial information tied to specific places, such as GPS coordinates, maps, or urban layouts from GIS systems.

- **Outcome**: This classification organizes the outcomes of smart city governance projects into three primary benefits, reflecting their impact on service delivery, operational efficiency, and democratic engagement:
  - **Improved Public Service**:
    - Personalized Services
    - Public (citizen)-centered services
    - Increase quality of public information and services
    - More responsive, efficient, and cost-effective public services
    - New services or channels
  - **Improved Administrative Efficiency**: Cost-reduction
    - Responsiveness of government operation
    - Improved management of public resources
    - Increased quality of processes and systems
    - Better collaboration and better communication
    - Reduced or eliminate the risk of corruption and abuse of the law by public servants
    - Enabled greater fairness, honesty, equality
  - **Open government capabilities**:

- Increased transparency of public sector operations
- Increased public participation in government actions and policy making

- Improved public control and influence on government actions and policies.

- **Smart city (SC) Taxonomy:** for better understanding that each project has been used in with part of urban planning, here is a classification:
  - **Smart Mobility**
  - **Lighting**
  - **Waste Management**
  - **Environmental and Land Monitoring & Management**
  - **Safety and Surveillance**
  - **Tourism & Entertainment Services**
  - **Smart Building & Smart Metering**
  - **Energy Communities**
  - **Citizen Services**
  - **Smart Government**
- **Smart city taxonomy sub scope:** more in detailed information of target application.
- **Database:** This indicator captures the diverse types of databases required for project implementation. It reveals which data types support specific AI domains:
  - Document-based
  - Geospatial / geodata
  - Administrative (registry, taxation, building, etc.)
  - Statistical and census
  - Multimedia (images, video, audio)
  - Health-related
  - Sensor / IoT (environment, traffic, consumption)
  - Citizen–government interactions (chatbots, service desks, reports)
  - Regulatory and legal
  - Synthetic / simulated
- **Geographic coverage – NUTS 2021**, refers to the EU's official territorial classification system used for statistics, regional analysis, and EU funding. NUTS, Nomenclature of Territorial Units for Statistics, maintained by Eurostat.

2.3.2. Data pre-processing

Once the data collection process was completed, to proceed with an effective data analysis, it was necessary to clean and preprocess the format of the collected data. This step was crucial to ensure a faster and more consistent subsequent analysis, primarily using Excel and its pivot table features. In the following there are preprocessing steps that have been done:

- **Accuracy and typo errors:** Special attention was given to correcting errors and spelling mistakes in columns, such as status and data scope. This meticulous checking ensured that Excel accurately interpreted aggregated data in pivot tables. Column names often had inconsistencies (like capitalization errors or trailing spaces) that caused Excel to misclassify the data. To resolve this, a filter was applied to select each unique name, which was then copied and pasted in a uniform format across all columns.

- **Empty cells management:** For empty cells, the underlying data context is first examined to determine whether the absence has semantic meaning (e.g., lack of information availability or an undefined classification in the predefined structure of the data source) or whether it represents missing data.

Columns related to the outcome, AI taxonomy, SC taxonomy, and database sections originally contained categorical markers, where "x" indicated selection and "NaN" indicated non-selection. For analytical consistency and to enable effective pivot-table analysis, these values were converted into binary format, with 1 representing selection and 0 representing non-selection.

2.4. Database analysis method

This section presents the methods and analytical dimensions adopted to provide a comprehensive mapping of the state of the art in smart city projects and to derive meaningful insights from the dataset. The first subsection introduces the dimensions of analysis, while the second subsection describes the analytical tools employed to carry out the analyses.

2.4.1. Analysis dimensions

The structure through which the analyses were conducted is divided based into thematic areas defined by different types of indicators, helping to face a deep and broad analysis on each aspect of the smart city context. The six dimensions are the following:

- Temporal Deployment maturity & Status
- Geographical and Governmental Level
- Database and Process Analysis
- AI Methodology and Smart city Domain
- Outcome

1. Temporal, Deployment maturity & Status

- **Number of projects per year:** indicator used to map the number of projects conducted each year from 2023 to 2025 in world.
- **Number of projects per different level of maturity:** This indicator classifies Smart City AI projects according to their developmental maturity, distinguishing whether a project is at the announcement stage, in proof of concept (PoC), or already operative. It reveals the overall evolutionary phase of AI implementation within the Smart City domain and indicates the degree to which these initiatives have progressed from conceptual planning toward full-scale deployment.

2. Geographical and Governmental Level analysis

The sample used for this kind of analysis is constituted by 393 projects resulting in a temporal time span between 2023 and 2025. The indicators included to perform the analysis are:

- **Percentage of projects per continent and countries:** this indicates distribution of the projects in the world (by considering that it depends on availability of the data and research method limitation.)
- **Number of projects per Geographical extent and distribution of different extent over 3 years**: Each project is implemented at a specific spatial scale (Local, Regional, National, or Multinational). This indicator is used to assess the scalability and maturity of AI-enabled Smart City projects by examining the extent to which solutions move beyond localized deployments toward broader territorial adoption and how it changes over time.
- **Number of projects per responsible organization category**: This indicator classifies projects according to the type of organization responsible for their implementation, including academic research institutions, central government bodies, consortia, local governments, and private-sector entities. It enables an analysis of the distribution of responsibilities and interactions among different societal actors, providing insight into governance structures, collaboration patterns, and the relative roles of public, private, and academic stakeholders in AI-enabled Smart City projects.
- **Project Status by Responsible Organization Category:** it indicates the distribution of smart city projects across responsible organization categories, segmented by project status (Announcement, Operative, Proof of Concept (PoC)). It provides insight into how different institutional actors engage with AI-enabled smart city initiatives at varying stages of maturity.

3. Database and Process analysis

- **Number of Projects by Government Interaction Type:** This indicator classifies Smart City AI projects according to the three primary modes of government interaction, government-to-government (G2G), government-to-citizen (G2C), and government-to-business (G2B). It highlights the nature and intensity of institutional relationships between government entities and other societal actors, offering insight into governance models, service delivery mechanisms, and the role of AI in facilitating public sector interaction within society.
- **Number of projects per process type:** The Process Type indicator captures how AI-enabled smart city projects are distributed across different types of societal and governmental processes.
- **Number of projects per Data scope**: This indicator categorizes Smart City AI projects according to the scope of data utilized, distinguishing among dynamic (real-time), historical, and location-based data. It enables an assessment of how different data scope types are employed in relation to project objectives and supports the identification of the key data characteristics required—such as timeliness, spatial granularity, and temporal depth—for effective AI implementation in Smart City contexts.
- **Frequency of databases type:** This indicator examines the frequency of use of different database types across Smart City projects, identifying which data storage and management technologies are most adopted. It highlights the critical role of data availability, infrastructure readiness, and data quality in enabling AI-driven Smart City solutions and reflects how technological choices align with project requirements

and operational constraints.

4. AI Methodology and Smart city Domain

- **Frequency of AI Method Usage across Smart City Projects:** This indicator shows how much AI techniques have been used across the projects.
- **Percentage of projects per smart city domain:** This indicator classifies AI-enabled Smart City projects according to their application domain (e.g., mobility, energy, environment, safety, citizen services), with the aim of identifying areas of greatest focus and investment. It highlights which urban domains attract the highest level of AI adoption and reflects societal priorities and problem severity, often driven by factors such as population growth, urbanization pressure, and service demand.
- **Usage of AI Taxonomy over Years**: This graph illustrates the temporal evolution of AI classification categories within the dataset from 2023 to 2025, showing how different AI system types change over time.
- **Number of Smart City Projects by Taxonomy Domain Over Time**: This indicator shows how the distribution of smart city projects across different taxonomy domains evolves over time.

5. Outcome analysis

- **Benefit Impact Distribution:** By counting how often project outcomes are associated with each benefit sub-classification, this indicator reveals the areas most affected by AI adoption, offering insight into whether Smart City initiatives primarily enhance service delivery, Administration efficiency, or transparency and participatory governance.

2.4.2. Analysis Tool

To support a concise and systematic analysis of smart city project data, this study employed pivot tables in Excel to aggregate, organize, and explore key patterns within the dataset. Pivot tables enabled flexible segmentation of projects across multiple analytical dimensions, such as application fields, benefit types, geographic distribution, and outcome frequency. Importantly, this approach allows all analyses and visualizations to be automatically updated in response to any changes in the underlying dataset, ensuring consistency, efficiency, and reproducibility throughout the analytical process.

3. Analysis and Results

This section of analysis is based on 393 projects that gathered for this thesis.

3.1. Temporal, Deployment maturity & Status

1. Number of projects over year

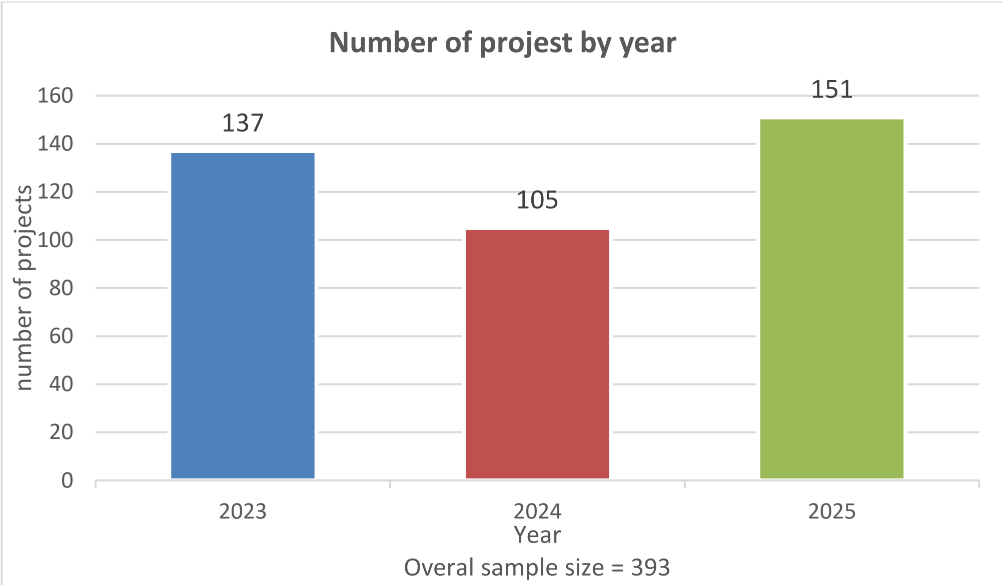


Figure 5: Number of projects over year

Figure 5 illustrates the annual number of projects conducted over 2023–2025.
Observed values:
- **2023:** 137 projects
- **2024:** 105 projects
- **2025:** 151 projects

2. Status of projects (Maturity) over year

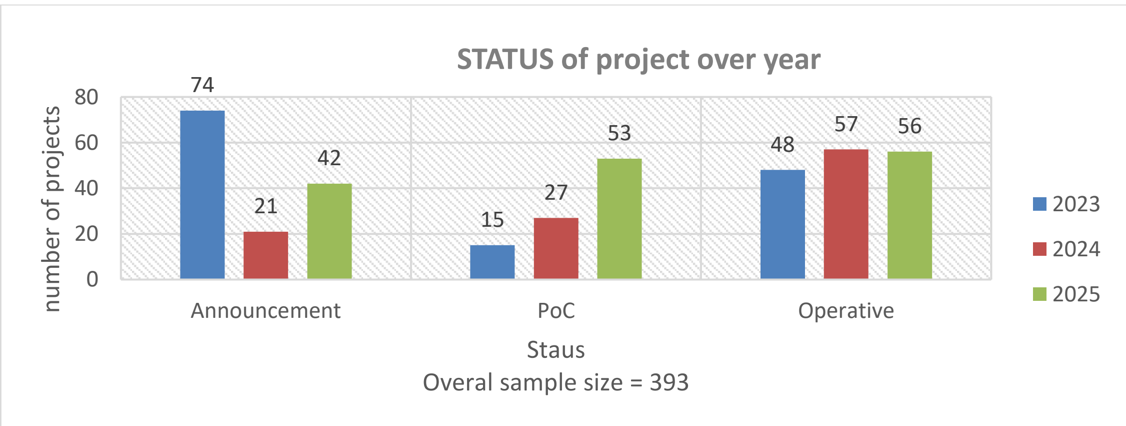


Figure 6:Maturity Status of the projects over year-

Regarding figure 6, across the three-year period, there is a clear shift from early-stage status **(Announcement)** toward experimentation **(PoC)** and implementation **(Operative)**. In 2023, the status of the projects is dominant by announcement, and it decrease over time compared to the Poc and operative. It may suggest a shift from idea to implementation, operatives remain stable over time, which may indicate institutional capacity to translate projects into real-world applications. The PoC shows growth trend which may refer to the **innovation activity** and starting deployment in small scale experimentation to minimize risk and prove the concept of working. In the macro scale, number of the projects in Operative state is 161, the Poc is 95, and Announcement is 137.

3.2. Geographical and Governmental Level analysis

1.1. Percentage of the projects per Continent

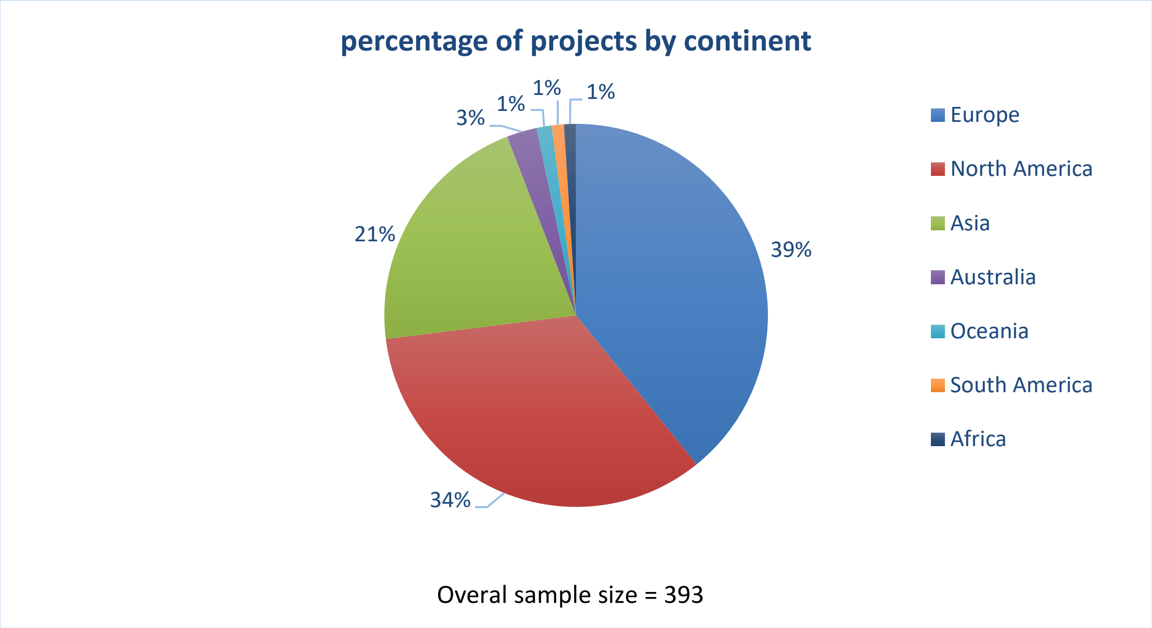


Figure 7: Percentage of the projects per Continent

In figure 7, three continents: Europe (39%), North America (34%), and Asia (21%), covered majority of the project's numbers. The project ecosystem is strongly centered in **economically advanced regions** which could suggest these are most innovative countries that put more effort and investment into the transformation of urban areas. In the following there is graph for top 10 countries regarding the number of projects inside the database:

1.2. Number of projects per Country (Top 10)

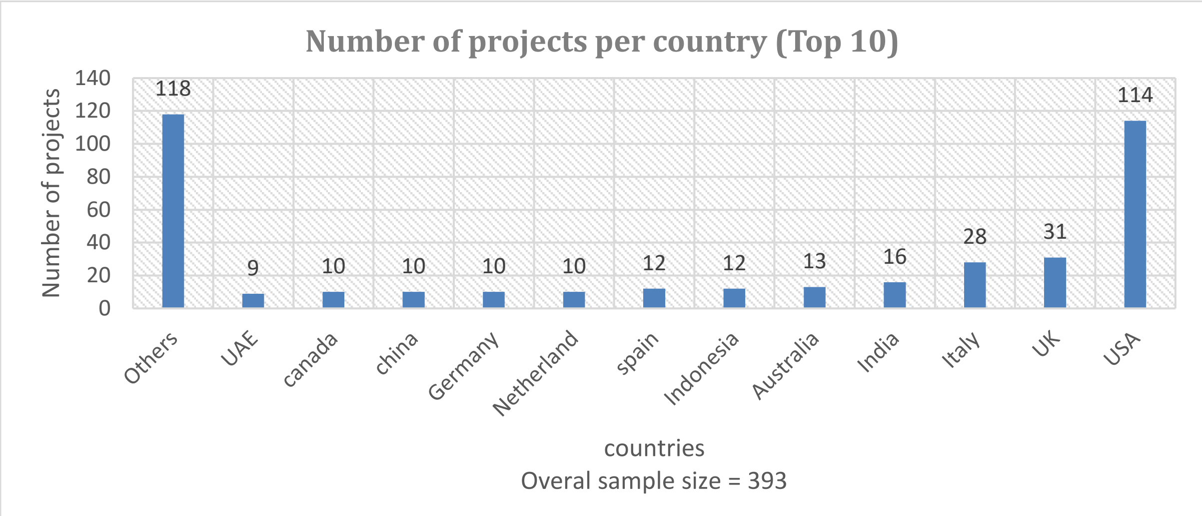


Figure 8: Number of projects per country (Top 10)

Figure 8 exhibits that in the North America, most of the projects concentrated on USA (114), in the second tier UK (31) and Italy (28) are in the top places among countries in Europe. The remaining countries show comparable project counts, each ranging between 10 and 15 projects.

2.1. Number of Projects per Geographical extent

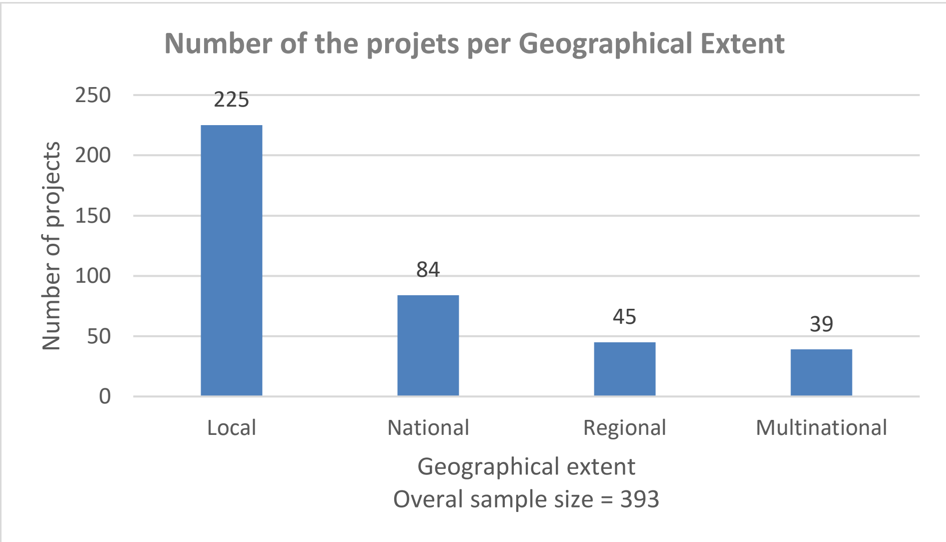


Figure 9: Number of projects per Geographical extent

Figure 9 illustrates the distribution of smart city projects by geographical extent, with Local projects accounting for 225 cases (57%), followed by National projects with 84 cases (22%), Regional projects with 45 cases (11%), and Multinational projects with 39 cases (10%). The predominance of local-scale projects may indicate that smart city initiatives are more frequently implemented at smaller geographical levels, where deployment, data availability, and stakeholder coordination could be relatively more manageable. National-level projects, representing the second largest category, may suggest an increasing interest by countries and central authorities in scaling solutions beyond individual cities, which could require more developed policy frameworks and coordination mechanisms. Regional projects, involving collaboration across multiple local jurisdictions, may reflect efforts toward inter-municipal cooperation, although their lower number could be associated with potential challenges related to governance alignment and interoperability. The comparatively limited number of multinational projects may reflect the higher complexity of cross-country initiatives, including regulatory diversity, coordination requirements, and increased implementation costs.

2.2 Changes of Projects per Geographical extent over 3 years

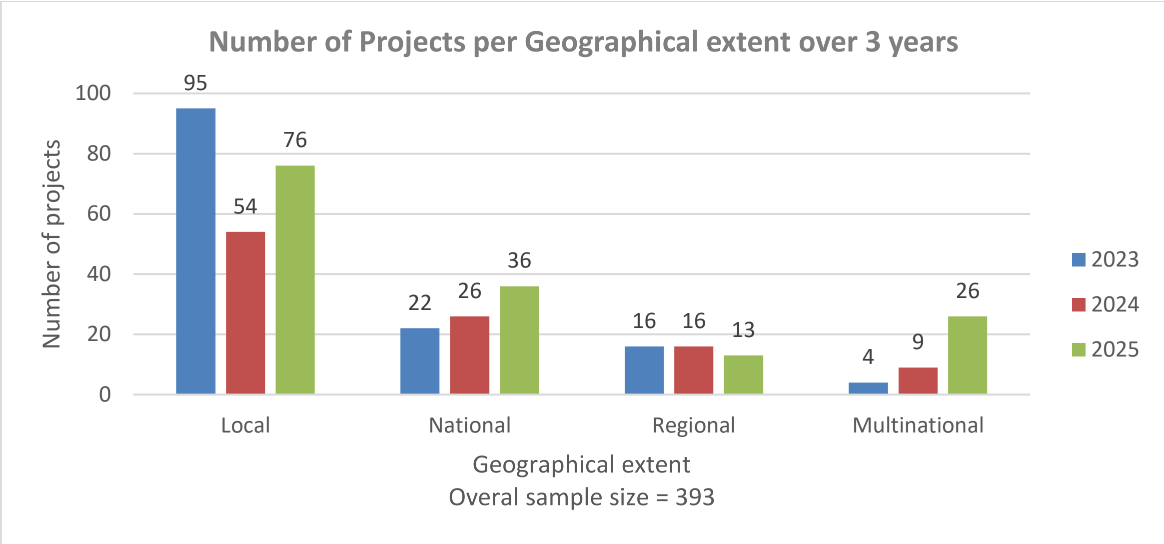


Figure 10: Number of Projects per Geographical extent over 3 years

Continuing the analysis of the previous part, figure 10 show changes of number of projects by Geographical extent between 2023 – 2025. While the Local scope experience a decline in 2024 to (54) but it increase again in 2025 to (76), on the other hand, number of projects increase at the National and multinational level over 3 years, which may indicate the upward trend in the world toward larger-scale, coordination, and scalability of the project reflecting move toward addressing the challenges of complexity and integration, and shared data infrastructures. Regional projects remain relatively stable.

3. Number of projects per Responsible Organization Category

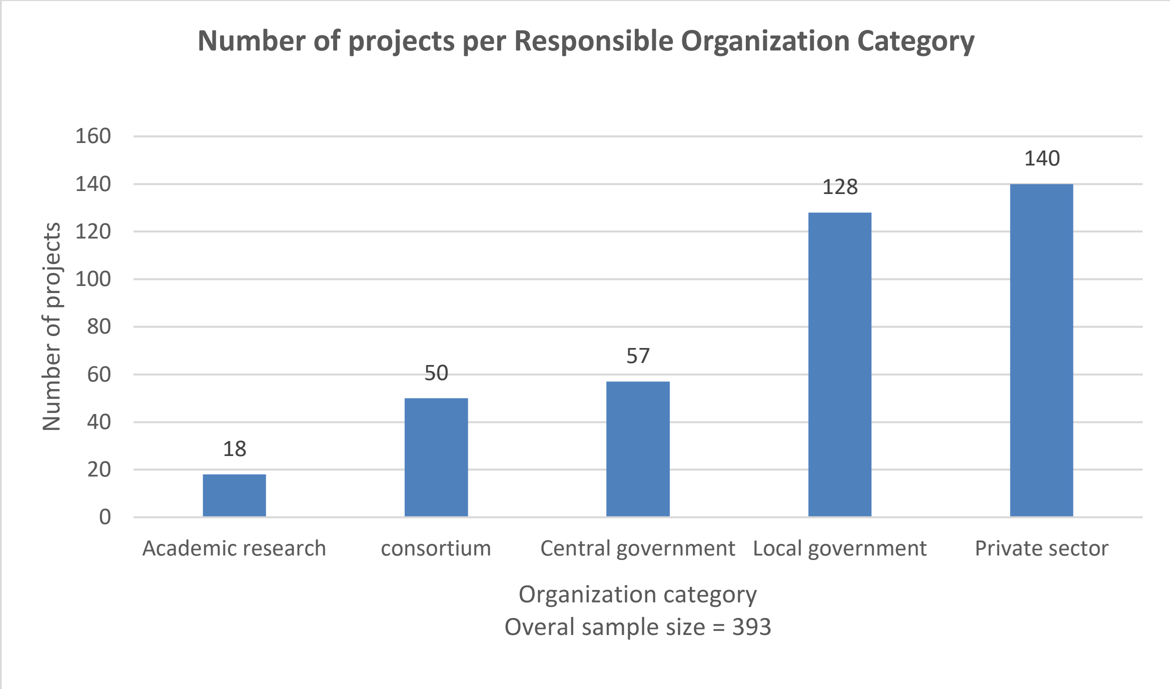


Figure 11: Number of projects per Responsible Organization Category

Regarding Figure 11, the distribution of responsible organizations shows that **private-sector actors (140 projects)** and **local governments (128 projects)** constitute the largest shares of the smart city initiatives analyzed, together accounting for more than two-thirds of the total. This distribution may reflect a project landscape that is predominantly local, practice-oriented, and focused on implementation. In many cases, AI-enabled smart city projects may be initiated in response to local policy priorities and deployed within clearly defined urban contexts, where decision-making processes, data access, and operational control could be relatively more manageable.

Central governments are responsible for **57** projects, ranking third among the identified actors. Their comparatively smaller share may suggest that large-scale, national deployment of AI-driven smart city solutions could remain constrained by institutional complexity, governance requirements, or infrastructural limitations.

Consortia account for **50** projects, placing them in fourth position. As formal cross-sector collaboration structures, their limited representation may highlight an underdeveloped yet potentially strategic dimension of smart city development, which could be influenced by the higher coordination, trust, and governance requirements associated with multi-actor partnerships.

Finally, **academic and research** organizations are associated with **18** projects, representing the smallest share in the distribution. This limited presence may indicate that most projects captured in the dataset are positioned in pilot, operational, or execution phases rather than in exploratory or research-driven stages. It could also suggest that academic involvement often occurs earlier in the innovation process, with research outcomes subsequently transferred to projects led by public or private sector actors.

4. Project Status by Responsible Organization Category

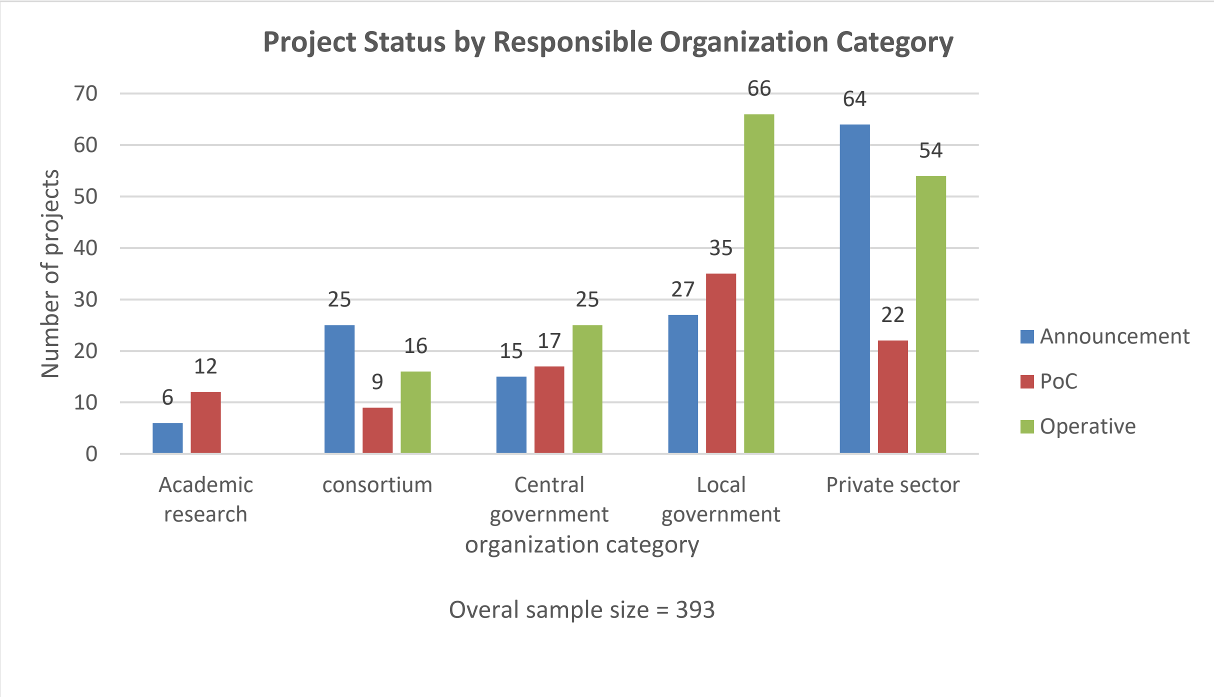


Figure 12: Project Status by Responsible Organization Category

As shown in Figure 12**,** local governments play a vital role in driving transformation in urban planning and smart city development. This is shown in the chart: most implemented (operative) projects belong to **local** authorities, followed by continuous announcements and proof-of-concept (PoC) activities. After local governments, the **private sector** appears as another strong contributor. It helps cities become "smart" by offering technology solutions and working closely with public institutions to scale projects in the future. The graph shows that many private-sector projects are **at the announcement stage**, but also a large number are already **operative**, confirming their active involvement. The **central government** has fewer projects but plays a **strategic role**—it supports and scales local initiatives to reach national levels through coordination and policies. **Consortia-based projects** focus mostly on **announcements** rather than operative or PoC stages, which may indicate that multi-partner collaborations are usually in the early planning phase because of their complexity. Lastly, **academic institutions** are mainly active in the **PoC stage**, with little involvement in large-scale operations. This shows their natural position as drivers of **experimentation and innovation** at early stages, rather than direct implementation.

3.3. Database and Process analysis

1. The interaction over different process types

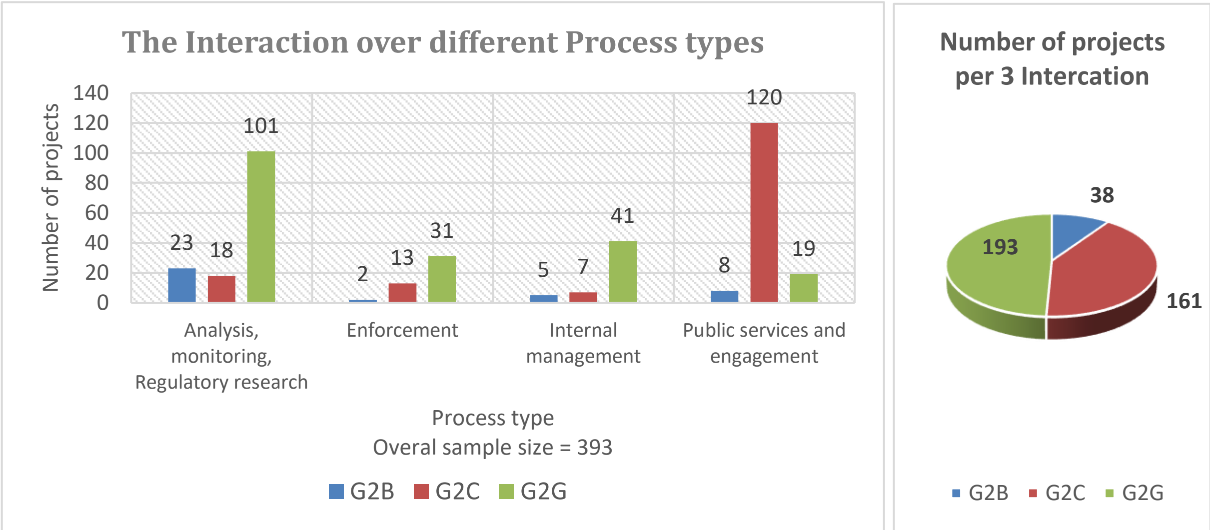


Figure 13: The distribution of Interaction over different process types

Figure 13 shows, based on 393 sample size, the distribution of the projects per Interaction of government: G2G is 193 which is highest, G2C is 161, and G2B is 38. In the left part of figure 13, the strong concentration of **analytical, monitoring, regulatory, enforcement, and internal management functions** within G2G interactions may indicate that core urban operations (such as traffic management, safety and surveillance, and infrastructure coordination) are primarily organized and executed by public authorities. By contrast, **government-to-citizen** (G2C) interactions are mainly associated with **public service delivery and engagement**, positioning citizens as recipients of optimized urban services rather than as direct participants in system control. **Government-to-business** (G2B) interactions remain comparatively limited across process types, could reflect that private actors are more often integrated as technology providers or operators within publicly governed frameworks than as co-managers of urban systems.

2. Database type and data scope distribution

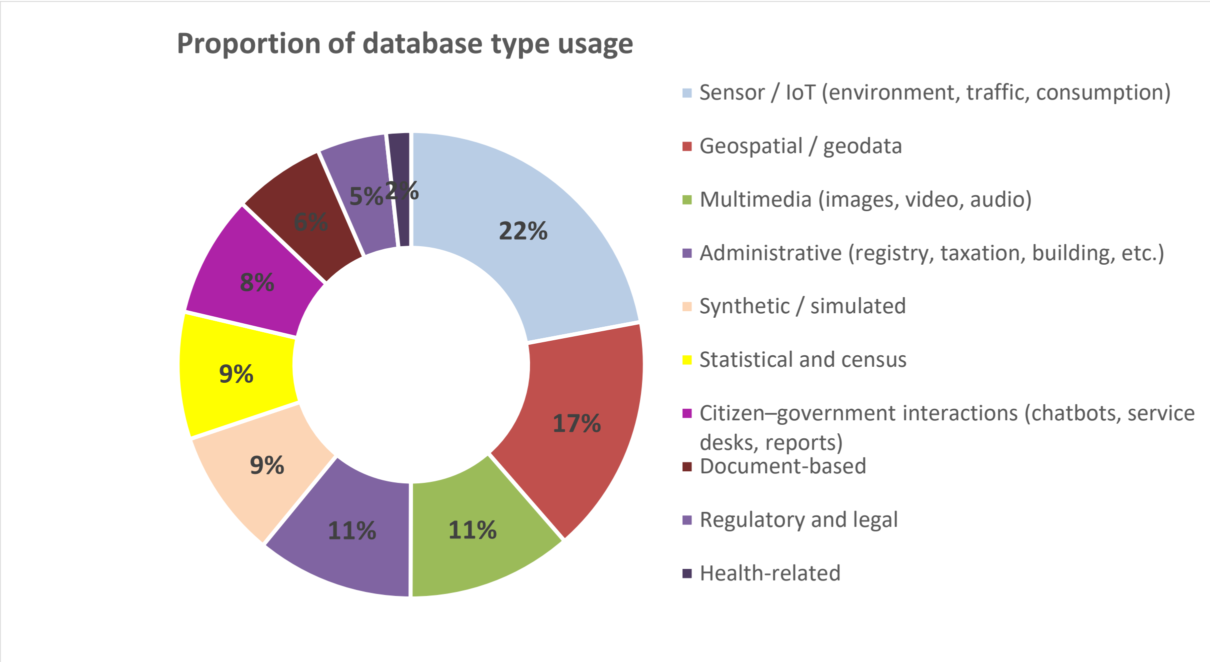


Figure 14: Proportion of database type usage in projects- sample size: 393

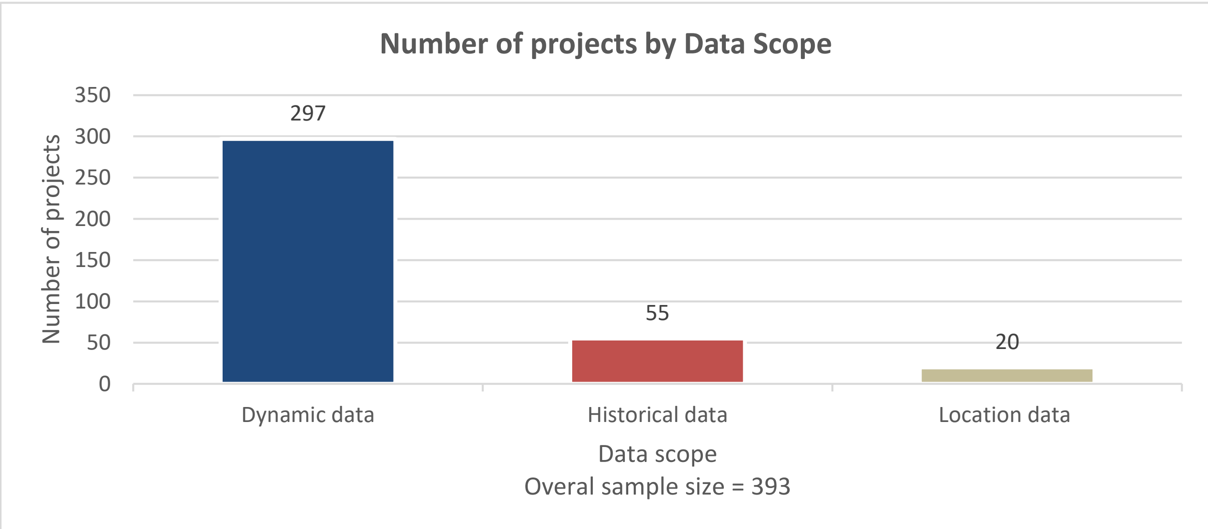


Figure 15: Number of projects by Data Scope

Database Type (Figure 14) shows percentage of database usage across projects.

- Sensor / IoT data is the most frequently used database type 22%
- Geospatial data follows 17%
- Administrative data and multimedia data each account for 11%
- Statistical/census and synthetic data each represent 9%.
- Citizen–government interaction data is 8%
- Document-based data is 6%
- Health-related data is low 2%

Data Scope (Figure 15)

- Dynamic data is dominant, used in 297 projects
- Historical data is used in 55 projects

- Location-based data appears in only 20 projects

When analyzed figures 14&15 together, the two graphs show a clear alignment between data scope and database type usage in smart city projects. The dominance of **Dynamic data** is closely linked to the frequent use of **sensor/IoT and geospatial databases**. This suggests that most smart city initiatives depend on real-time and continuously updated data to monitor and manage urban systems such as traffic, environment, and safety.
Databases related to historical data (administrative (11%), statistical/census (9%) and documentary (6%)) are mostly static or with periodic updates. More often used in long-term analysis, policymaking and performance evaluation.
The low use of administrative, statistical and documentary databases may reflect their limitations in responding to the real-time needs of the agile smart city. These results could show the importance of data availability, data quality and scalable data infrastructures as key factors in the selection of data type and database.

3.4. AI Methodology and Smart city Domain

1. Frequency of AI Method Usage across Smart City Projects

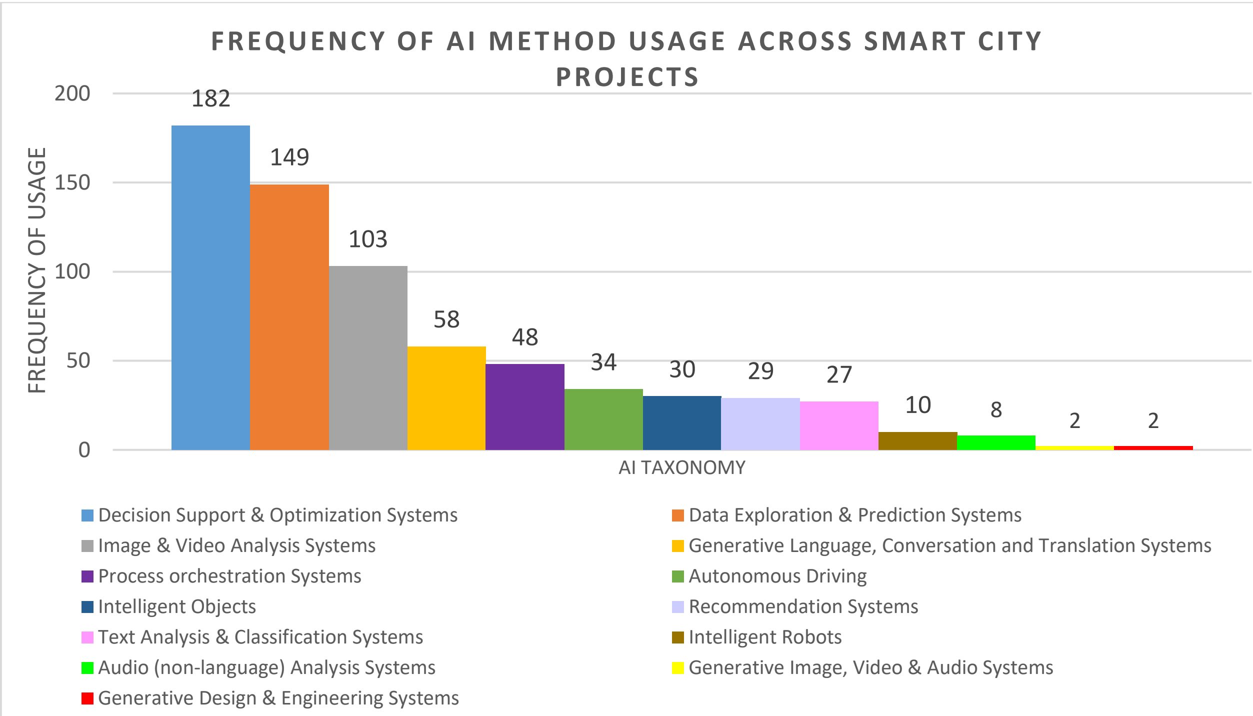


Figure 16: Frequency of AI Method Usage across Smart City Projects-sample size 393

Based on figure 16, the distribution of AI method usage across smart city projects shows how artificial intelligence is operationalized in urban contexts. Analytical and decision-making approaches (Decision Support & Optimization Systems and Data Exploration & Prediction Systems) dominate the portfolio, indicating that important role of AI is enhancing human decision-making, planning, and resource optimization rather than enabling full system autonomy. For the monitoring and visual analysis (image & video analysis system), it placed third place. Furthermore, interactive AI methods, including language-based systems, process orchestration, recommendation, and text analysis, exhibit moderate but consistent usage, suggesting their role as enabling layers that facilitate communication, coordination, and service integration. Finally, embodied and physical AI (such as autonomous driving, intelligent objects, robotics, and generative engineering) remains comparatively low, highlighting persistent technical, regulatory, and economic barriers to large-scale deployment of autonomous and hardware-embedded intelligence in cities.

2. Percentage of projects per smart city domain

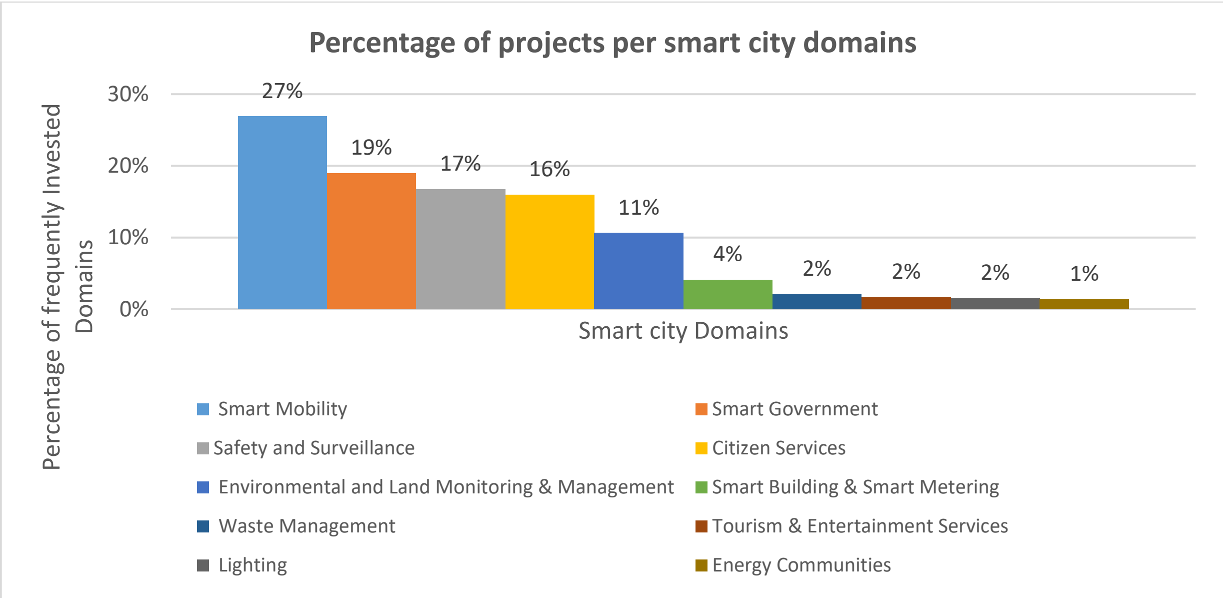
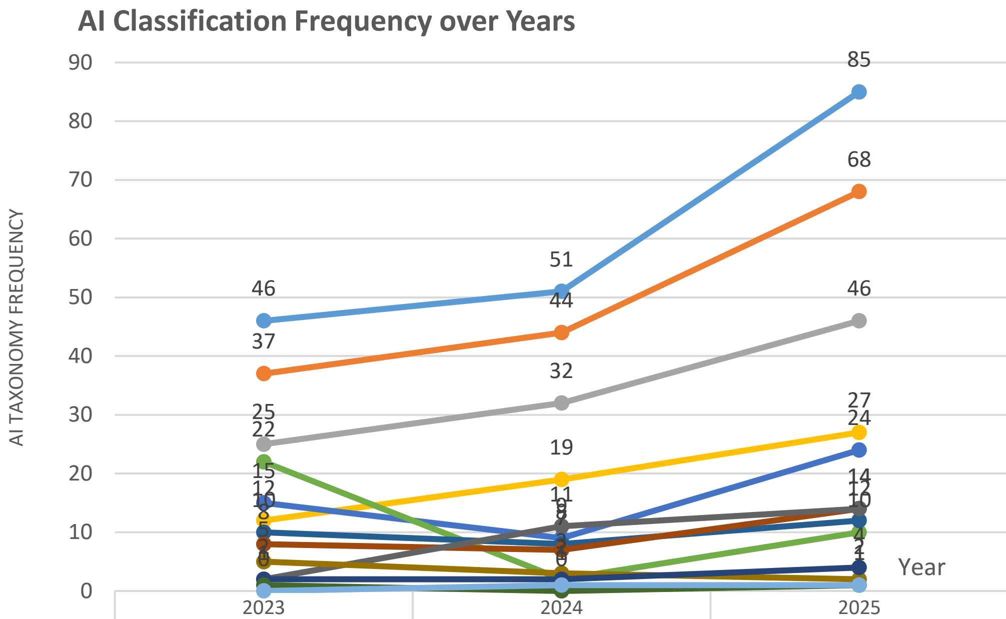


Figure 17: Percentage of projects per smart city domains- sample size: 393

This figure 17 shows the percentage of projects across different smart city domains which indicates which urban domains receive more attention and investment within the smart city project portfolio. Regarding the figure 14, Smart Mobility accounts for the largest share of projects (27%), which indicate that transportation and traffic optimization remain the primary focus of smart city initiatives, followed by Smart Government (19%), Safety and Surveillance (17%), and Citizen Services (16%). Environmental and Land Monitoring & Management represents a moderate share (11%), while Smart Building & Smart Metering remains limited (4%). Energy Communities (1%), Tourism & Entertainment Services (2%), Lighting (2%), and Waste Management (2%) together form the lowest portion of the portfolio.

3. Frequency of AI Taxonomy over Years

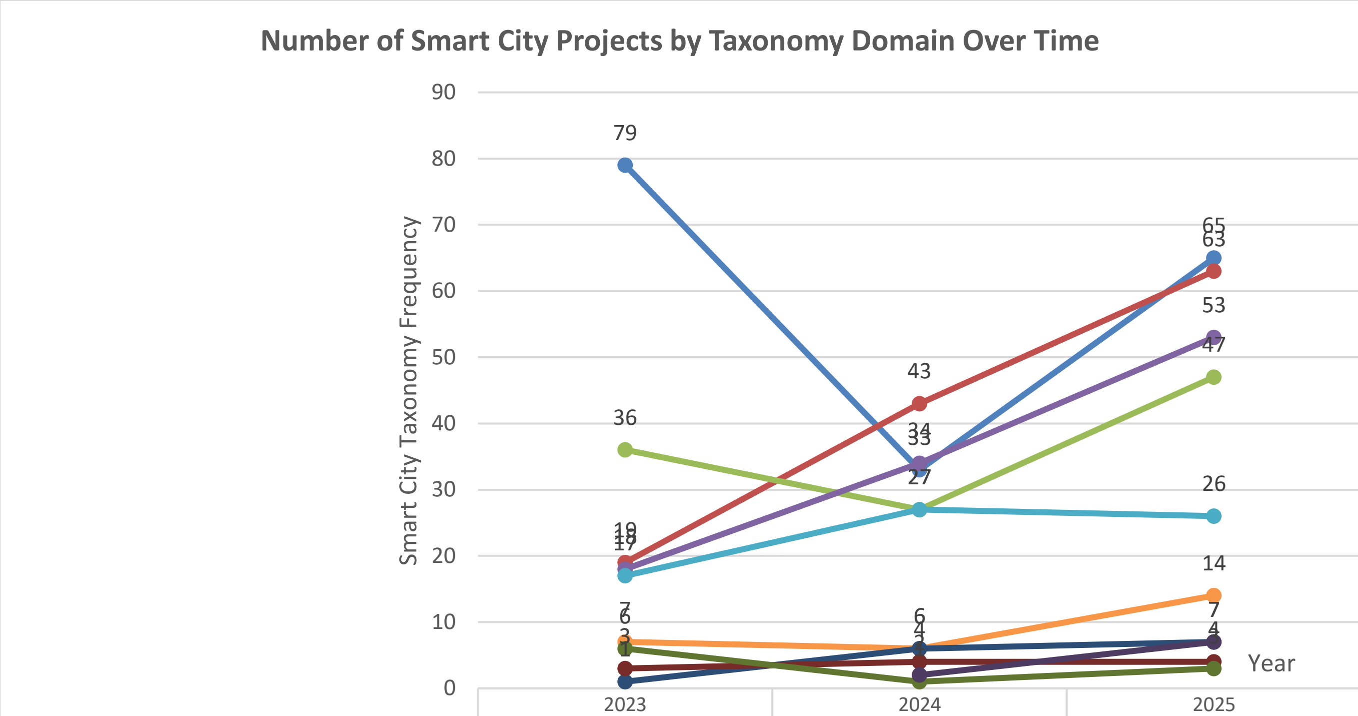


	2023	2024	2025
Decision Support & Optimization Systems	46	51	85
Data Exploration & Prediction Systems	37	44	68
Image & Video Analysis Systems	25	32	46
Generative Language, Conversation and Translation Systems	12	19	27
Process orchestration Systems	15	9	24
Autonomous Driving	22	2	10
Intelligent Objects	10	8	12
Recommendation Systems	8	7	14
Text Analysis & Classification Systems	2	11	14
Intelligent Robots	5	3	2
Audio (non-language) Analysis Systems	2	2	4
Generative Image, Video & Audio Systems	1	0	1
Generative Design & Engineering Systems	0	1	1

Figure 18: Frequency of AI Classification over Years-sample size: 393

In figure 18, most AI categories show a clear upward trajectory. The results show a shift toward **analytical and decision-oriented AI systems** in smart city projects. The strong growth of “decision support & predictive systems” and “data exploration & optimization” indicate increasing demand for AI that can support real-time planning, optimization, and operational decisions. The rise of image and video analysis reflects expanded use of visual data for monitoring and safety. Generative language systems grow at a moderate range, suggesting that conversational and language-based AI is becoming more relevant, but still plays a secondary role compared to analytical systems. In contrast, the decline of autonomous driving systems suggests higher technical, regulatory, or deployment barriers in urban environments.

4. Number of Smart City Projects by Taxonomy Domain Over Time



	2023	2024	2025
Smart Mobility	79	33	65
Smart Government	19	43	63
Safety and Surveillance	36	27	47
Citizen Services	18	34	53
Environmental and Land Monitoring & Management	17	27	26
Smart Building & Smart Metering	7	6	14
Waste Management	1	6	7
Tourism & Entertainment Services	3	4	4
Lighting	6	1	3
Energy Communities		2	7

Figure 19: Number of Smart City Projects by Taxonomy Domain Over Time- sample size:393

The top five smart city domains reveal a shift toward **governance, service, and system-oriented applications**. Regarding the figure 19, the overall trend shows a significant increase in the frequency of the smart city taxonomy domains between 2023 and 2025. While Smart Mobility experienced an initial sharp drop from 79 in 2023 to 33 in 2024, it recovered in 2025 (65) to remain among the domains with the highest frequency, although it is closely followed by Smart Government (63) and Citizen Services (53) in 2025. Safety and Surveillance also experienced steady growth (36 to 47), while domains such as waste management, lighting and tourism have maintained a very low frequency.

3.5. Outcome Analysis

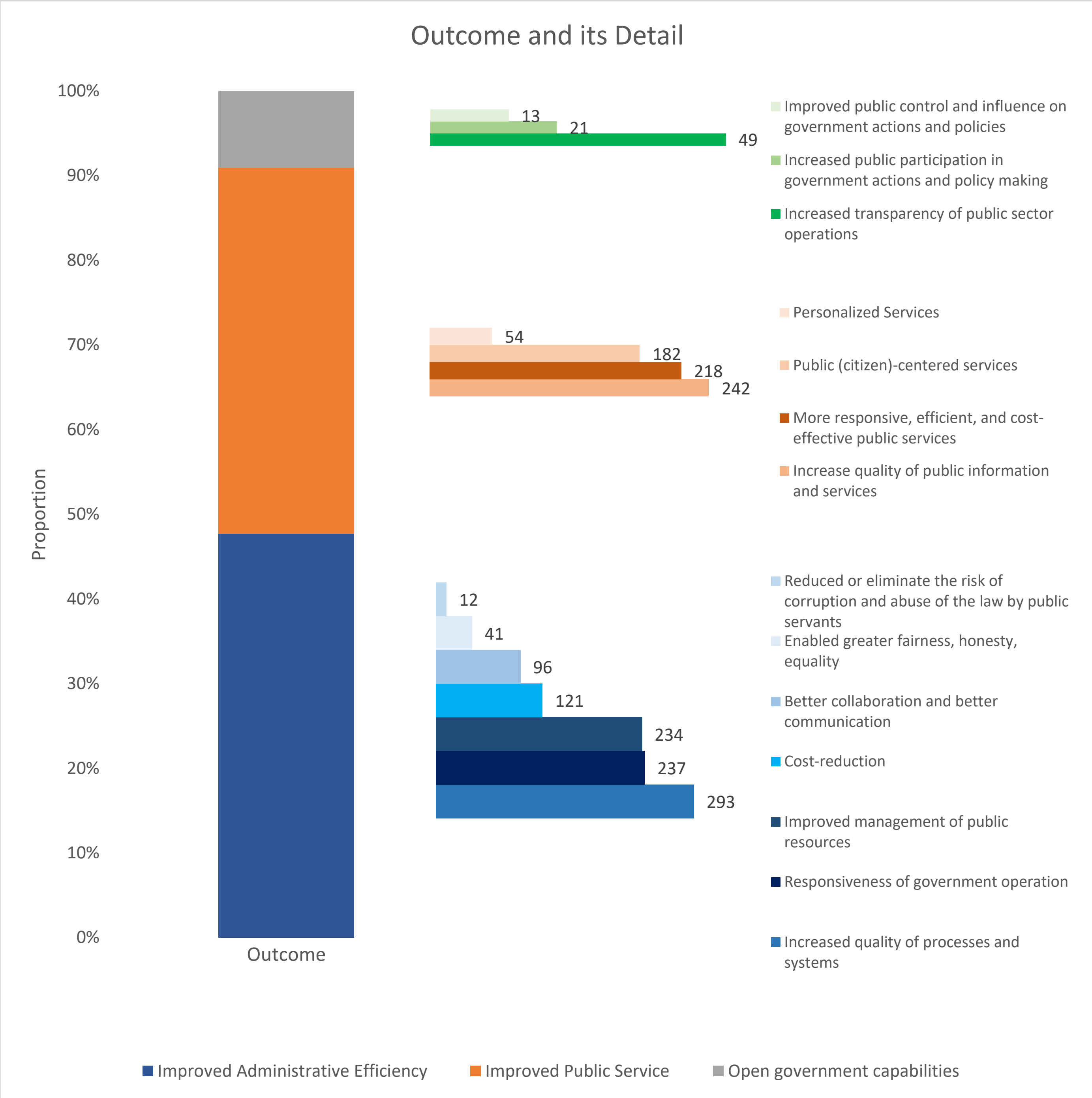


Figure 20: outcome classification- sample size:393

The project outcomes are classified into three main categories, reflecting the societal domain in which each project generates benefits. Accordingly, the outcomes are grouped into the following three classes:

- Improved Public Service. This refers to initiatives that are aimed at enhancing the quality of public services for the final user (citizen or business) by for example improving accessibility and ease of access to the service or the overall quality of the public service provided.
- Improved Administrative Efficiency. This includes purposes of efficiency, effectiveness, increasing quality, and lower cost for administrative processes, systems, and services keeping government operations systematic, sustainable, flexible, robust,

lean and agile, better management of public resources and economy.

- Open government capabilities. This refers to impacts on openness, transparency, participation, communication, and collaboration to provide personal or corporate influence and control on government actions or policy[5]

Figure 20 shows the main outcomes of smart city AI projects (*Improved Administrative Efficiency*, *Improved Public Service*, and *Open Government Capabilities*.) and their sub-categories. The vertical stacked bar on the left represents the distribution of three main outcome categories.
The horizontal bars on the right break down each main outcome into specific sub outcomes, showing how often each detailed outcome appears across projects.

Stacked Vertical Bar (Left) shows category frequency:

- Improved Administrative Efficiency 352 (blue): ~48%
- Improved Public Service 319 (orange): ~42%
- Open Government 67(Gray): ~10%

Horizontal Bars (Right) - Legend Order:

Administrative Efficiency (Dark blue):
- Increased quality processes/systems: 293
- Responsiveness government operations: 237
- Improved management public resources/economy: 234
- Cost-reduction: 121
- Better collaboration/cooperation: 96
- Enable fairness, honesty, and quality: 41
- Reduced corruption risk: 12

Public Service (orange):

- Increased quality public info/services: 242
- More responsive/efficient/cost-effective services: 218
- Public centred services: 182
- Personalized service: 54

Open Government (Gray):

- Transparency public operations/actions: 49
- Citizen participation policy: 21
- Public control/influence government policy: 13

[5] AI Watch. European landscape on the use of Artificial Intelligence by the Public Sector

4. Mixed-Method Analysis

Complexity framework

While the previous descriptive analysis reveals the distribution of AI initiatives across smart city domains, it does not address the varying degrees of socio-technical complexity that significantly influence governance and implementation strategies. Simple single-domain tools require different deployment approaches compared to integrated, multi-AI, multi-domain systems. **The goal of this framework** is to classify projects according to **integration complexity along two axes**: how wide the project's scope spans across smart city domains (Narrow: 1 domain, Moderate: 2 domains, Broad: 3+ domains), and how broad the AI methods are in terms of functional classes used (Lightweight: 1 class, Intensive: 2+ classes). This scope-AI breadth matrix reveals implementation patterns and maturity trajectories across 393 projects.

4.1. Defining Axes

4.1.1. Horizontal axis: project scope (Narrow, Moderate, Broad)

Project's scope is derived from the number of smart city taxonomies that project included. In the excel file defined 10 domains (**Smart Mobility - Lighting - Waste Management - Environmental and Land Monitoring & Management - Safety and Surveillance - Tourism & Entertainment Services - Smart Building & Smart Metering - Energy Communities - Citizen Services - Smart Government**). After analysis of the frequency of different combinations of smart city domains across the projects, it shows that most two-domain combinations occur with relatively high frequency generally reflect functionally related or share outcome rather than complex cross-sector integration. Typical examples include projects jointly addressing Smart Mobility and Safety and Surveillance (e.g., road safety and traffic monitoring), or Citizen Services and Smart Government or Environmental and Land Monitoring & Management and Smart building, these 2 Domains have in common value.

Based on this observation, regarding to this dataset, projects involving one domain considered as Narrow, and two domains are classified as Moderate scope because it does not necessarily imply ecosystem-level integration. In contrast, projects spanning more than two domains are classified as Broad (ecosystem) scope, as they indicate a wider and more systemic impact across multiple parts of the city.

- Narrow: 1 domain flagged
- Moderate: 2 domains flagged
- Broad: 3 or more domains flagged (multi-domain projects affecting several parts of the city)

Dataset information:

- Narrow: 199 (51%) projects
- Moderate: 143 (36%) projects
- Broad: 51 (13%) projects

4.1.2. Vertical axis: AI breadth (Lightweight vs Intensive)

Since the number of AI methods does not adequately reflect technical complexity. Therefore, AI methods are classified into functional groups based on their primary role and capabilities. In the Excel file, 12 AI methods are defined. The following section explains the rationale and criteria used for their classification. Project's complexity can be defined as "how many of these classes are combined":

- Proposed AI method classes

1. Generative & Interface AI
2. Perception & Sensing AI
3. Analytical & Decision AI
4. Autonomous & Embodied AI

Table 5: Proposed AI Method class 1-4

Class	Methods	Rationale
Class 1: Generative & Interface AI	1- Generative Language, Conversation and Translation Systems 2- Generative Image, Video & Audio Systems 3- Generative Design & Engineering Systems	• Create new content (text, code, images, designs) rather than just analysing existing data. • Typically sit at the interface with humans: chatbots, assistants, content generation, scenario design.
Class 2: Perception & Sensing AI	1- Text Analysis & Classification Systems 2- Image & Video Analysis Systems 3- Audio (non-language) Analysis Systems	• Perceive and interpret raw signals: text, images, video, audio. • Convert unstructured inputs (documents, camera feeds, sounds) into structured information (objects, labels, events). • Require higher data volume and throughput. • Demand advanced data governance (especially vision/audio).
Class 3: Analytical & Decision AI	1- Data Exploration & Prediction Systems 2- Recommendation Systems 3- Decision Support & Optimization Systems 4- Process Orchestration Systems	• Core analytical engines: discover patterns, forecast outcomes, propose actions, optimise resource allocation, orchestrate workflows. • Often operate on structured data (tabular logs, sensors, administrative records).
Class 4: Autonomous & Embodied AI	1- Autonomous Driving 2- Intelligent Robots 3- Intelligent Objects	• Act in the physical world: vehicles, robots, smart assets that sense, decide, and execute actions. • Combine perception + planning + control. • Introduce safety-critical and liability considerations. • Require integration with infrastructure (roads, buildings, logistics systems) and regulatory frameworks. • Involve safety, regulation, physical integration, maintenance, and often multiple stakeholders (transport authorities, operators, citizens).

This grouping method fits the complexity / integration goal: complexity is not just "more methods", but more layers of the AI pipeline combined in one project, so AI-complexity levels are:

- **Lightweight technical**: 1 class
- **Intensive technical**: 2 or more classes

Dataset information:

- Lightweight technical 282 (71%) projects
- Intensive technical 111 (29%) projects

4.2. The Scope × AI breadth Matrix

Based on the dimensions defined in the previous section, six archetypes emerge. By crossing project scope with the breadth of AI methods applied, we obtain a matrix that reflects different levels of integration complexity. The distribution of cases across this matrix is as follows:

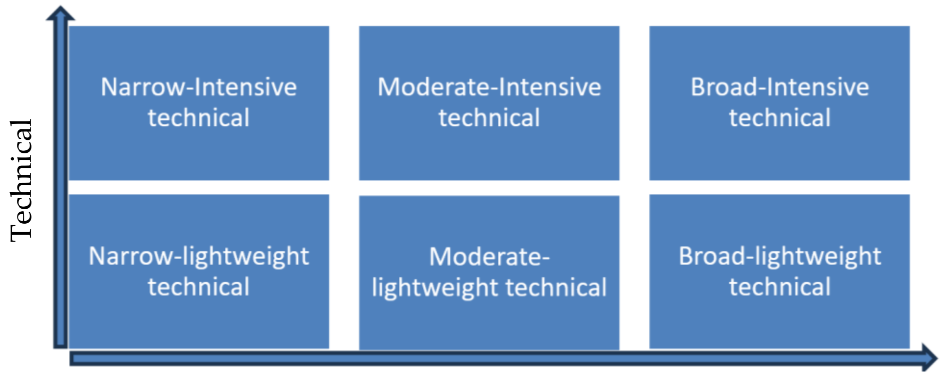


Figure 21: Qualitative Analysis Matrix- AI × Scope

Table 6: project classification based on 6 Archetypes

	Narrow	Moderate	Broad	Grand Total
Intensive Technical	55	34	22	282
Lightweight Technical	144	109	29	111
Grand Total	199	143	51	393

In terms of difficulty there are **two dimensions of risk**:

- **Technical difficulty**: using multiple AI classes at once (Generative & Interface, Perception & Sensing, Analytical & Decision, Autonomous & Embodied)
- **Organizational difficulty**: how many domains means **how many departments/actors** must coordinate

With that lens, each cell in the matrix has a different complexity profile:

1- Narrow + Lightweight Technical

- 144 projects in dataset fall into Narrow-lightweight group
- Single domain, 1 AI class
- Implementation difficulty: lowest, One owner, clear boundaries, limited integration

Case: *Hobbs,USA: AI-Powered Gun Detection System (ZeroEyes)*

Year: 2023

Source: https://www.govtech.com/public-safety/hobbs-n-m-will-roll-out-an-ai-powered-gun-detection-system

Hobbs, USA has deployed ZeroEyes' AI-powered gun detection system across city cameras to enhance public safety, building on its successful year-long use in local schools. The software analyzes existing CCTV feeds for illegally brandished firearms, instantly alerting a 24/7 team of military/law enforcement veterans at ZeroEyes' Operations Center, who verify threats and dispatch actionable intelligence (gun type, description, location) to police within 3-5 seconds. Managed by the Hobbs Police Department's Real-Time Crime Center, the system distinguishes real threats from toys like Airsoft guns, with a $22,500 annual 60-month contract; early results show detections without false alarms on legal carry, positioning it as a proactive tool against gun violence while complementing street patrols.

Focus detection task, existing infrastructure, minimal AI sophistication.

1. **Narrow scope (1 domain)**:
   - Safety and Surveillance Domain
   - Layered on existing cameras → no cross-domain integration
   - Single owner: Hobbs Police Department
2. **Lightweight Technical (1 AI class)**:
   - Perception & Sensing AI only: visual gun detection (Image & Video Analysis)
   - No other classes: no prediction, no optimisation, no generative interface, no autonomy
   - Simple pipeline: detect → human verification → alert

2- Narrow + Intensive Technical

- 55 projects in dataset fall into Narrow-Intensive group
- Single domain but combines 2+ AI classes (like sensing + analytical + interface)
- Example: traffic system with cameras (Perception) + prediction and optimisation (Analytical) + interface dashboard (Generative/Interface)
- Implementation difficulty:
  - High technically
  - Moderate organizationally

This is where administrations **push technical limits in a controlled environment**.

Case: *Indosat launches AI-based surveillance for enterprises*

Year: 2025

Source: https://developingtelecoms.com/telecom-technology/enterprise-ecosystems/18755-indosat-launches-ai-based-surveillance-for-enterprises.html

Indosat Ooredoo Hutchison launched Vision AI, a modular AI-based surveillance platform for Indonesian enterprises on July 10, 2025, designed to enhance operational efficiency and security through real-time event analysis and early warnings. The solution combines AI-ready cameras, 3D stereo sensors, and a customizable training platform to detect patterns, monitor high-risk areas, count traffic, analyze customer behavior, and integrate with existing CCTV systems—all processed locally using sovereign AI infrastructure. Scalable for SMEs to multinationals, it supports use cases like proactive public space security and retail analytics, with Indosat emphasizing privacy protection and responsiveness as key advantages over traditional surveillance.

Vision AI demonstrates the Narrow + Intensive Technical archetype: a single-domain security solution combining multiple AI classes for real-time enterprise monitoring. Proactive security, operational efficiency.

1- Narrow scope (1 Domain):

- Safety and Surveillance domain for enterprises.

2- Intensive Technical (+2 AI classes):

- Perception & Sensing AI: AI-ready cameras + 3D stereo sensors for real-time event capture
- Analytical & Decision AI: pattern detection, risk/opportunity alerts, traffic counting, customer behaviour analysis
- Generative & Interface AI: customizable AI training platform, early warnings

3- Moderate + Lightweight technical

- 109 projects in dataset fall into Moderate-lightweight group
- Two domains (ex: Mobility + Environment), simple AI (1 class)
- Example: shared analytics across transport and pollution using prediction only.
- Implementation difficulty:
  - Low–medium technically
  - Medium organizationally: requires coordination between two units, common data model, shared governance

This cell looks like the **integration-first strategy**: cities start to connect domains using **simple AI**, to learn how to coordinate data and responsibilities before adding more complex models.

Case: *Sunshine Coast Council deploys AI avatar for customer service*

Year: 2025

Source: https://www.govtechreview.com.au/content/gov-tech/news/sunshine-coast-council-deploys-ai-avatar-for-customer-service-1720119235?utm_source=feedly

Sunshine Coast Council (Australia) is trialling AI avatar "Laura" through a 3-month pilot under Invest Sunshine Coast's Testing Tech in Paradise program, deploying a computer-generated kiosk in Maroochydore City Centre to handle basic customer service queries. Using gaming tech, motion sensors, microphones, ChatGPT speech recognition, and lifelike facial expressions, Laura answers general council FAQs (damaged bins, collection days, office locations, pet registration, libraries, maintenance reports) drawn from public website data, but cannot access personal records or track service requests, keeping it strictly informational.

1. **Moderate scope (2 domains)**: **Smart Government** (council services) + **Citizen Services** (public enquiries)
2. **Lightweight Technical (1 class)**: its core technology is **Generative & Interface AI** (ChatGPT avatar)

4- Moderate + Intensive technical

The count is smaller than in Moderate + Low Technical, which suggests that not all integrations are ready for heavy AI, cities selectively choose which cross domain problems justify this investment.

- 34 projects in dataset fall into Moderate-lightweight group
- Two domains + multiple AI classes
- Implementation difficulty:
  - cross-department governance
  - multi-class AI
  - shared infrastructure

Case: *City of Las Vegas: Vapor IO Kinetic Grid Edge AI Platform*
Year: 2023
Source:https://www.smartcitiesworld.net/ai-and-machine-learning/ai-and-machine-learning/bringing-pervasive-ai-to-the-edge-for-the-city-of-las-vegas
The City of Las Vegas partnered with **Vapor IO** to deploy **pervasive edge AI** via the Kinetic Grid platform, initially in the **Medical District**, using private 5G and computer vision to enable real-time applications like traffic management, public safety, crowd monitoring, and predictive maintenance of utilities. The system processes data at the edge for **microsecond latency decisions**, setting a precedent for smart city transformation globally, with Michael Sherwood (Chief Innovation Officer) emphasizing its role in modernizing infrastructure through instantaneous AI-driven responses.

1- Moderate scope (2 Domains):

- Safety (crowd monitoring, security)
- Smart Mobility/Infrastructure (traffic management)

2- Intensive Technical (2 classes):

- Perception & Sensing AI: computer vision analysing real-time video feeds.
- Analytical & Decision AI: pervasive edge AI for instantaneous processing (traffic,

maintenance).

5- Broad + Lightweight technical

These are governance experiments: strong emphasis on organizational integration and shared data, while keeping the AI layer intentionally light to reduce technical risk. Good candidates for platform/infrastructure foundations.

- 28 projects in dataset fall into Broad-lightweight group
- Three or more domains, 1 class of AI.
- Implementation difficulty:
  - High organizationally (many owners, data sources, priorities)
  - Low technically

Case: *Urban Intelligence as a Modular Digital Twin Ecosystem*
Year: 2024
Source: https://www.agendadigitale.eu/smart-city/cnr-il-modello-di-urban-intelligence-per-la-scienza-delle-citta/

The Urban Intelligence (UI) model developed by CNR proposes a modular Urban Digital Twin (UDT) architecture designed to support cities of all sizes, from large metropolitan areas to small municipalities. Rather than treating digitalisation as an end goal, the model frames it as an enabling infrastructure for strengthening collective intelligence, multi-actor governance, and inclusive urban planning.
The architecture decomposes the city into thematic subsystems, such as mobility, built environment, water systems, and green infrastructure, each represented through a Thematic Digital Twin. These modules are built using scientific models, data sources, and simulation tools. Through APIs, the modules are interconnected and then integrated with AI-based systems (like machine learning) that analyse cross-sector interactions. This enables a systemic understanding of the city as a complex, interdependent organism.
The model is adaptable to varying levels of technological maturity. It integrates with existing sensor networks, databases, smart services, and infrastructures, supporting a co-construction process with local stakeholders. A key principle is human-scale technology: maintaining human control over analytics and decision support while embedding civic participation into the knowledge-building process.

1- Broad scope (3+ Domains):

- Smart Mobility
- Environmental and Land Monitoring & Management
- Smart Building & Smart Metering
- Smart Government

2- Lightweight Technical (1 classes):

- Decision support and optimization system

- Data Exploration & Prediction Systems

6- Broad + Intensive technical

These are best interpreted as **urban AI platforms** or **digital twin ecosystems**, where perception, decision, and interface capabilities are integrated across several policy areas. Their small number reflects the **high barriers to implementation and coordination**, but their presence shows that a few administrations are already operating at this frontier.

- 23 projects in dataset fall into Broad-Intensive group
- Three or more domains + multiple AI classes (like: sensing + prediction + optimisation + interface).
- Implementation difficulty, highest:
  - multi-department coordination
  - complex AI models

Case: *AI-Driven Intelligent Traffic Infrastructure in Maryland*
Year: 2024
Source: https://www.smartcitiesworld.net/ai-and-machine-learning/maryland-to-use-ai-technology-to-manage-traffic-flow

BizzTech and Atlas Traffic Technologies formed a strategic partnership to combine immersive digital twin environments with real-time AI-driven traffic analytics. The collaboration aims to support next-generation smart city and smart campus infrastructure through integrated, data-driven platforms.
The solution merges Atlas's real-time traffic intelligence and predictive analytics with BizzTech's interactive digital twin technology. The result is a unified environment where urban systems can be visualised, analysed, simulated, and optimised in near real time.
Born from the University of Colorado Denver Smart Futures Lab initiative, the partnership focuses on enhancing public safety, reducing congestion, enabling sustainable infrastructure planning, and accelerating smart city innovation globally. Urban planners and government agencies can use immersive simulations and predictive insights to support data-informed strategic decisions and long-term infrastructure development. This is not just traffic management. It is a digital representation of the city fused with AI-driven foresight.

1- Broad scope (3+ Domains):

- Smart Mobility
- Environmental sustainability
- Safety and surveillance
- Smart Government

2- Intensive Technical (1+ classes):

- Image & Video Analysis Systems
- Decision support and optimization system
- Data Exploration & Prediction Systems

4.3. Overall insight

The matrix shows that organisational integration is the primary constraint: most projects remain Low Technical and/or Narrow or Moderate in scope, where implementation is easier. Technical intensity is more often added within single domains first (Narrow Intensive) and only later in a small subset of Broad projects that attempt full ecosystem integration. It supports the idea that smart-city AI maturity follows two trajectories:

- A **"tech-first" trajectory**, where sophisticated AI is developed inside individual domains and only later scaled across domains; and
- An **"integration-first" trajectory**, where cities first connect multiple domains with simple AI and only then add more advanced capabilities.

5. Conclusions

This chapter brings together the main results of the thesis and provides an overall summary of how artificial intelligence is being applied in smart city projects around the world. Building on the objectives introduced at the beginning, to understand **where and how AI technologies are implemented**, **which actors and governance levels are involved**, and **what outcomes they produce**, the findings offer a consolidated picture of the current state of the art.

The analysis combined quantitative data exploration with a qualitative framework to study different urban domains, such as mobility, energy, buildings, safety, government, and tourism. This approach made it possible to identify patterns in project distribution, levels of maturity, and the main priorities guiding AI investment and adoption.

The chapter first outlines the **main findings** that emerged from the dataset analysis, followed by the **limitations** of the study, and **future research directions** aimed at improving coordination, governance, and the long-term scalability of AI-driven smart city systems.

Main findings

1. Smart City AI Projects Are Fundamentally Data-Driven and Real-Time Oriented
The first finding of this study is the strong reliance of AI-enabled smart city projects on dynamic, real-time data, primarily supported by sensor/IoT and geospatial databases. This reflects a dominant operational logic focused on monitoring, control, and immediate response in domains such as mobility, environment, and safety. In contrast, historical and administrative datasets (statistical, documentary, census-based) play a secondary role, reflecting their limitations in responding to the real-time needs of the agile smart city. These results emphasize the importance of data availability, data quality and scalable data infrastructures as key factors in the selection of data type and database.

2. AI in Smart Cities Is Primarily Decision Supportive, Not Autonomous

Across the portfolio, analytical and decision-oriented AI methods (decision support, optimization, prediction, and data exploration) dominate. AI is mainly used to augment human decision-making, improve planning, and optimize resources rather than to replace human control. Embodied and autonomous AI systems (e.g., robotics, autonomous driving) remain marginal, reflecting high deployment risk, regulatory barriers, and infrastructural complexity.

3. Investment Concentrates on Mobility, Governance, and Service Delivery

The distribution of projects across smart city domains reveals clear social and institutional prioritization. Smart Mobility remains the most invested domain, but Smart Government, Citizen Services, and Safety & Surveillance show strong growth, indicating a shift toward governance- and service-oriented applications.

4. Smart City AI Is Scaling Geographically, but Governance Lags Behind

Although local-level projects dominate the dataset, a clear upward trend is observed in national and multinational initiatives, suggesting a move toward scalability and coordination. However, the relatively low presence of central governments and consortia indicates persistent institutional and governance barriers to large-scale integration.

The ecosystem is largely shaped by local governments and private-sector actors, together accounting for more than two-thirds of projects. Local governments lead operational deployment, while the private sector plays a key enabling and implementation role. Academic institutions appear mainly at early or experimental stages, and Consortia remain limited in their presence, despite their strong potential to address complex challenges across multiple urban domains.

5. **AI Maturity Follows Two Distinct Development Trajectories**

The qualitative archetype matrix reveals two dominant paths toward AI maturity:

- a **tech-first trajectory**, where advanced AI is developed within a single domain before broader integration; and
- an **integration-first trajectory**, where multiple domains are connected using simpler AI before increasing technical intensity.

Most projects remain narrow in scope and low-to-moderate in technical intensity, suggesting that organizational integration, rather than AI capability, is the primary bottleneck. Ecosystem coordination is a stronger constraint than algorithmic sophistication.

6. Outcomes Prioritize Efficiency Over Democratic Engagement

The outcome analysis shows that most AI-enabled smart city projects aim to improve administrative efficiency and public service delivery. Outcomes related to open government, transparency, and citizen participation are significantly less frequent.

Overall, the findings indicate that AI-enabled smart city development is driven by real-time data availability, decision-support technologies, and locally grounded implementation, while facing persistent challenges related to governance coordination, data access, citizen engagement, and ecosystem-wide integration.

Limitations

The data collection process relied on publicly available online sources and information. While this approach enabled the compilation of a broad and diverse dataset, it does not constitute a comprehensive overview, as it was inherently constrained by the availability, accessibility, and quality of public information, as well as by the person's search capacity. The identification and documentation of AI use cases were particularly dependent on how clearly projects described their technological components.

A further limitation concerns the definition and boundaries of artificial intelligence within the collected projects. In several cases, projects did not explicitly refer to "AI" but instead described the use of related techniques such as machine learning, algorithms, or data-driven models. This made it challenging to identify whether a project should be classified as an AI application. In addition, as AI is used as an umbrella term and in some cases as a keyword (and often a buzzword) for journalistic or marketing purposes, it was not always easy to distinguish whether a certain case is using AI or not.

Another definitional challenge concerns the concept of the **public sector**. This issue is particularly relevant for domains such as health, economic affairs (e.g., energy, transport, agriculture), environmental protection, education, and public safety, which are discussed within the public-sector context. However, it is not always clear whether an organization should be classified as public or private. In addition, many organizations operate within a **hybrid public–private space**, including entities that are partially or fully government-owned, further complicating classification. These ambiguities may lead to some misclassification or uncertainty regarding the inclusion or exclusion of specific cases. It is assumed that such issues do not introduce systematic bias into the overall analysis.

The Mixed-Method analysis based on the six-archetype matrix is subject to several limitations related to the definition of analytical axes and the classification of projects. First, the delineation of project scope, expressed through the number of involved domains, and the assessment of AI complexity were based on an interpretive judgment informed by the conceptual understanding of ecosystem challenges, coordination requirements, and governance structures. While this perspective is theoretically grounded and consistent with the study's analytical framework, it inevitably reflects a degree of subjectivity.

Second, for reasons of analytical clarity and comparability, all application domains and AI methods were considered with equal impact weight when classifying projects within the matrix. This simplifying assumption does not capture potential differences in the relative impact, maturity, or strategic importance of specific domains or AI techniques. As a result, the framework prioritizes structural positioning and pattern identification over fine-grained performance or effectiveness evaluation.

Practical implication Future direction

- **Public administration:**

The findings indicate that the main bottleneck in AI-enabled smart city development is not technological capability but institutional coordination. Public administrations should therefore prioritize national and regional coordination mechanisms to move beyond fragmented local pilots toward interoperable and scalable ecosystems. National governments play a critical enabling role in defining common data standards, regulatory frameworks, funding schemes, and procurement guidelines that allow local projects to integrate into broader infrastructures rather than remain isolated initiatives.

Regional and national coordination bodies can facilitate knowledge transfer, shared platforms, and cross-city data architectures, reduce duplication and increase scalability. Without such coordination, smart city AI risks remaining operationally effective but structurally fragmented.

At the same time, multinational collaboration earns greater attention. As AI systems increasingly operate across borders—particularly in domains such as mobility, climate monitoring, cybersecurity, and digital services—harmonized regulatory approaches and interoperable standards become essential.

In this perspective, governments are not merely project implementers but ecosystem architects. Their strategic role is to create the institutional conditions under which AI systems can evolve from isolated deployments into integrated, resilient, and cross-border smart city infrastructures.

- **Private sector:**

The findings suggest that private firms should not position themselves solely as technology providers, but as long-term partners within multi-level smart city ecosystems. Given that AI-enabled smart city projects depend on interoperability, scalable data infrastructures, and coordinated governance frameworks, private actors play a dual role: technological innovators and collaborative system integrators.

As technology providers, firms are responsible for developing modular, interoperable, and standards-compliant solutions that can integrate across municipal, regional, and national platforms. Designing systems that support data portability, transparency, and long-term maintainability is essential to avoid fragmentation and vendor lock-in, which undermine scalability.

At the same time, collaboration with the public sector is vital. AI deployment in smart cities operates within regulatory, ethical, and political environments that require co-design rather than unilateral technological implementation. Private firms should therefore engage in structured partnerships with public administrations, contributing technical expertise while aligning with public accountability requirements, data governance standards, and societal objectives.

In this ecosystem perspective, the private sector's competitive advantage lies not only in algorithmic sophistication but in its ability to operate within coordinated governance architectures and support cross-level integration. Sustainable impact will depend on firms' capacity to collaborate with public institutions in building scalable, interoperable, and ethically grounded AI infrastructures.

In summary, this thesis seeks to understand how artificial intelligence is applied in the current landscape of smart cities. By analyzing various projects across different domains that leverage AI to enhance efficiency and responsiveness in an increasingly dynamic world, it highlights that digital transformation and technological alignment are not the sole indicators of "smartness." Numerous barriers must also be addressed — from data accessibility and infrastructure limitations to administrative and governance challenges. Ultimately, this thesis examines two conceptual dimensions of complexity faced by smart city projects. Future research could therefore move beyond algorithmic performance to focus on institutional readiness, as discussed in the mixed-methods which low number of broad-intensive technical projects indicate to the unexplored area of scalability.

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