POLITECNICO MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

EXECUTIVE SUMMARY OF THE THESIS

AI and Smart City: Smart Technologies for Future Cities

TESI MAGISTRALE IN MANAGEMENT ENGINEERING – INGEGNERIA GESTIONALE

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ACADEMIC YEAR: 2025-26

1. Introduction

Global urbanization is a critical trend, by 2024 more than half of the world's population lived in cities, and this share is expected to reach 68% by 2050. In this context, smart cities are framed as a strategic response to environmental pressures, resource constraints, and rising demand for efficient, sustainable, and equitable urban services.

This section introduces Smart Cities and Artificial Intelligence (AI) as foundational enablers of urban transformation and sets the stage for the subsequent discussion of the broader smart-city ecosystem. [1][2]

1.1 Artificial Intelligence

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.

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** is the foundational capability enabling AI systems to learn from data and support prediction, optimization, and decision-making without explicit programming. In smart cities, ML underpins data-driven governance by forecasting demand, identifying risks, and optimizing resource allocation across domains such as mobility, energy, and public safety. **NLP** enables AI systems to understand and generate human language, serving as the primary interface between citizens and digital city services. Its core role lies in improving accessibility, responsiveness, and service efficiency through applications such as chatbots, virtual assistants, automated reporting, and multilingual communication. **Deep Learning** provides advanced analytical power for processing complex, unstructured data through multi-layer neural networks. It is critical for high-impact smart-city applications that require precision and scale, including autonomous mobility, advanced surveillance, facial recognition, and large-scale urban and satellite image analysis. **Computer Vision** allows AI systems to interpret visual data from cameras and sensors, transforming images and video into actionable intelligence. Its primary role in smart cities is real-time situational awareness, supporting traffic monitoring, public safety, infrastructure inspection, and autonomous systems. **Data Mining** extracts actionable insights from large and heterogeneous datasets by identifying patterns, correlations, and anomalies. In smart cities, it supports strategic planning and operational decision-making. [3][4][5][6]

Smart cities integrate IoT, cloud computing, big data, 5G, digital twins, and AI to optimize urban operations across transport, energy, public safety, and environmental management, with AI amplifying these technologies into a unified, high-impact intelligent ecosystem. **The six-layer smart city architecture** shows how artificial intelligence is integrated with IoT sensors, communication networks such as 4G/5G, data management platforms, and cloud and edge computing to transform raw urban data into intelligent actions. IoT devices collect real-time data, which is transmitted through high-speed networks and processed using big data technologies and cloud infrastructure. AI algorithms analyze this data to support prediction, optimization, and automated decision-making, while digital twins use AI models to simulate and test urban scenarios. Together, these technologies operate as an integrated ecosystem that enables efficient, data-driven management of urban services.

1.2 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.

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 environmental sustainability.

A key area of interest in smart city research is the analysis of application fields, which can be structured into nine core domains that collectively cover the main aspects of urban optimization. These domains include Smart Mobility, Smart Lighting, Smart Waste Management, Smart Environmental Monitoring, Smart Buildings, Safety and Surveillance, Smart tourism, Smart Metering and Grids, Smart Government. Across these areas, smart city projects are primarily driven by the goals of improving quality of life, enhancing sustainability, and increasing operational efficiency through more intelligent use of limited urban resources. At the same time, their implementation faces significant challenges, including high deployment costs, privacy and security concerns, limited citizen adoption, data heterogeneity from large sensor networks, and the need to ensure the reliability and quality of collected data.

2. Objectives and Methodology

The main aim of this thesis is to explore and analyze the current state of the art in the role of artificial intelligence within smart cities.

To support the analysis, a detailed Excel database was created on smart city initiatives across 3 years 2023-2025. The columns defined in the dataset to be used are Usa case name, source, description of the case, progress status, start year, Geographical information (including geo extent, country, continent name), Governmental level and function (Responsible organization name and category), AI classification technics, process type, Interaction of Government, Data scope, outcome and impact of the case, Smart City Taxonomy, database type.

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 five dimensions are the following:

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

3. Analysis and Result

Temporal and Maturity Status

Projects peaked in 2025 (151), after a drop in 2024 (105) from (137) in 2023. In the macro scale, number of the projects in Operative state is 161, the Poc is 95, and Announcement is 137. 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.

Geographical and Governmental Level analysis

Distribution of the project across **continent** shows Europe (39%), North America (34%), and Asia (21%), covering 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.

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. 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. Across the time, number of multinational projects increase from 4 to 26 in 2025 may reflect move toward addressing the challenges of complexity and integration, and shared data infrastructures.

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. Central governments are responsible for 57 projects, ranking third. 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. Many private-sector projects are at the announcement stage, but also a large number are already operative, confirming their active involvement in developing the smart city goals like technology provider and investor.

Database and Process analysis

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. By looking at the interaction over **process type** (Analysis and monitoring, Enforcement, Internal management, and public service and engagement), 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.

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 distribution:

- Dynamic data is dominant, used in 297 projects
- Historical data is used in 55 projects
- Location-based data appears in only 20 projects

The two results 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.

AI Methodology and Smart city Domain

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.

Distribution of the smart city domains shows 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.

Outcome

Outcome Analysis: Project outcomes fall into three categories—**Improved Public Service** (319 projects, 42%: quality/accessibility for citizens/businesses), **Improved Administrative Efficiency** (352 projects, 48%: streamlined operations/resource management), and **Open Government Capabilities** (67 projects, 10%: transparency/participation).

4. Mixed-Method Analysis

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 **Six Archetypes** (project counts):

1. **Narrow-Lightweight**: 144 (lowest complexity)
2. **Narrow-Intensive**: 55
3. **Moderate-Lightweight**: 109
4. **Moderate-Intensive**: 34
5. **Broad-Lightweight**: 28
6. **Broad-Intensive**: 22 (highest complexity)

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

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. Conclusion

In conclusion, this thesis offers an in-depth analysis of the application of artificial intelligence in smart city projects worldwide from 2023 to 2025. The primary areas of focus include Smart Mobility, Smart Governance, and Smart Safety, with a particular emphasis on analytical and decision-making approaches such as Decision Support & Optimization Systems and Data Exploration & Prediction Systems. The findings highlight substantial public sector engagement, especially at the local level, accompanied by a growing interest and participation from private sector actors.

Limitation

The study's data collection relied on publicly available online information, providing a broad but not exhaustive dataset. Its scope was limited by the availability, quality, and clarity of public data and by the researcher's search capacity. Identifying AI use cases proved challenging, as many projects did not explicitly label their technologies as "AI" and often used related or ambiguous terms like machine learning, algorithms, or data-driven systems. This blurred definition risked inconsistent classification, especially given AI's frequent use as a marketing or buzzword.

Similar ambiguities arose in defining what constitutes the "public sector," particularly in domains such as health, energy, and education, where public and private roles often overlap. Some misclassifications or uncertainty in inclusion was therefore possible, though not expected to bias results.

The mixed-method analysis using the six-archetype matrix faced interpretive limitations. Project classification and AI complexity assessments involved subjective judgments, and all domains and AI methods were weighted equally for clarity and comparability. This approach favoured identifying structural patterns over measuring detailed performance differences.

Practical implication and Future direct

Public and Private actors play pivotal role in expanding and shaping smart city goals, Collaboration together could leverage their potential in creating solution and its expansion.

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. In addition, 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.

Overall, the thesis explores how AI is applied in smart cities across various domains, revealing that digital transformation alone does not define "smartness." Challenges such as data accessibility, infrastructure, and governance remain central. Future research could therefore move beyond algorithmic performance to focus on institutional readiness of scalability, as discussed in the mixed-methods, low number of broad-intensive technical projects indicate to the unexplored area of scalability and complexity of integration.

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