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Research on the Application of Artificial Intelligence Technology in Smart City Construction—An Analysis Based on Collaborative Scenarios of Traffic Management, Urban Energy, and Public Safety

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Abstract: With the continuous growth of urban governance targets, data scale, and operational constraints, traditional informatization models are no longer sufficient to meet the requirements of smart cities for real-time perception, collaborative decision-making, and refined governance. This paper systematically reviews the current application status, existing obstacles, and optimization paths of artificial intelligence (AI) in smart city construction, focusing on three high-frequency scenarios: traffic management, urban energy, and public safety. Based on English literature from the past three years, international city rankings, and relevant OECD statistics, an analytical framework of "data-algorithm-scenario-governance" is constructed. The study argues that AI has gradually shifted from single-point identification and local prediction to cross-departmental collaboration, digital twin simulation, and human-centered governance optimization; however, significant shortcomings remain in areas such as data silos, algorithm reliability, institutional coordination, cost constraints, and citizen participation. Therefore, this paper proposes a layered data governance model, scenario-based model deployment, a closed-loop reliability assessment system, and a multi-stakeholder co-governance mechanism to improve the efficiency, resilience, and sustainability of smart city construction.

1 Introduction

As the construction of new urbanization and Digital China continues to advance, smart cities have evolved from simply building information infrastructure to an integrated upgrade encompassing governance performance, public services, and urban resilience. Faced with complex situations such as traffic congestion, energy fluctuations, environmental pressures, public safety risks, and population mobility, urban management increasingly relies on real-time processing of massive amounts of heterogeneous data and intelligent decision-making. The technological advantages of artificial intelligence in perception and recognition, time-series prediction, pattern mining, anomaly detection, and autonomous collaboration are key forces driving smart city construction into a deeper governance phase.

In recent years, research on smart cities and artificial intelligence has accelerated significantly. Existing research has been conducted from four perspectives: policy governance, application scenarios, algorithm mechanisms, and city evaluation. Ben Rjab et al. systematically reviewed the barriers to the adoption of artificial intelligence in smart cities and found that institutional, organizational, technological, and ethical barriers often coexist [1]. Dong et al. analyzed about 3,700 papers using natural language processing methods and found that topics such as service transformation, community participation, sustainable development, data openness, and risk governance are becoming research hotspots. Son believes that algorithmic urban planning is prompting the transformation of urban governance from experience-driven to data-driven, but its effective implementation requires cross-stakeholder cooperation and high-quality data resources.

Based on the above background, this paper specifies the topic as "Research on Artificial Intelligence Empowering Smart City Construction Based on Collaborative Scenarios of Traffic Governance, Urban Energy, and Public Safety," mainly answering three questions: What is the current status and evolutionary characteristics of artificial intelligence in smart city construction? What are the key issues affecting the in-depth development of artificial intelligence? How to formulate an implementation strategy that considers both technological effectiveness and governance credibility? This paper follows a logical structure of current status analysis, problem identification, problem-solving or strategy implementation, and conclusions.

2. Current Status Analysis of the Research Topic

In terms of technology spectrum, the application of artificial intelligence in smart cities is no longer simply the use of a single algorithm model, but a combination of multiple technologies. Deep learning has improved the accuracy of video stream, remote sensing image, and urban acoustic data recognition. Reinforcement learning and heuristic optimization are suitable for complex traffic control and resource allocation. Machine learning, combined with graph computing, knowledge graphs, and digital twins, has begun to create a comprehensive decision-making system for urban operations. Wolniak and Stecuła summarized the current applications into six aspects: smart governance, smart transportation, smart environment, smart life, smart economy, and smart population, and believed that AI has moved from "tool support" to "platform empowerment". Hammoumi et al. used artificial intelligence methods to identify and classify 200 cities around the world, and further explained that the evaluation of smart cities is also being reshaped by AI methods [5].

Artificial intelligence (AI) is primarily applied to traffic management through traffic flow prediction, signal control optimization, event detection, and travel guidance. By integrating data from intersection cameras, floating car systems, and traffic signal controllers, five-minute congestion warnings and timing adjustment suggestions can be generated, improving traffic efficiency and reducing emissions. In urban energy scenarios, AI is used to enhance the resilience and economy of energy systems through building energy consumption prediction, power load balancing, distributed energy coordination, and equipment anomaly warnings. In the field of public safety, video recognition, risk assessment, group behavior analysis, and anomaly pattern detection enhance the ability to respond to emergencies, fire hazards, security incidents, and infrastructure damage. Lartey and Law believe that while AI has potential in decision support and policy formation, it has not yet been fully implemented in urban planning and governance.

In terms of international practice, the creation of smart cities is currently in a development process of "scenario-driven—data aggregation—governance closed loop." According to data released by the OECD, between 2023 and 2025, the proportion of OECD companies utilizing artificial intelligence rose from 8.7% to 20.2%, indicating that companies are adopting AI at an increasingly rapid pace. This provides external support for the intelligent upgrades of urban public sectors and municipal platforms. Furthermore, the IMD Smart City Index 2024 shows that Zurich, Oslo, Canberra, Geneva, and Singapore rank in the top five. High-level smart cities generally possess digital infrastructure, public service responsiveness, and good governance coordination.

Table 1. IMD Smart City Index 2024 top cities

Rank	City	Country/Region	Category
1	Zurich	Switzerland	Europe
2	Oslo	Norway	Europe
3	Canberra	Australia	Oceania
4	Geneva	Switzerland	Europe
5	Singapore	Singapore	Asia
6	Copenhagen	Denmark	Europe
7	Lausanne	Switzerland	Europe
8	London	United Kingdom	Europe
9	Helsinki	Finland	Europe
10	Abu Dhabi	UAE	Middle East

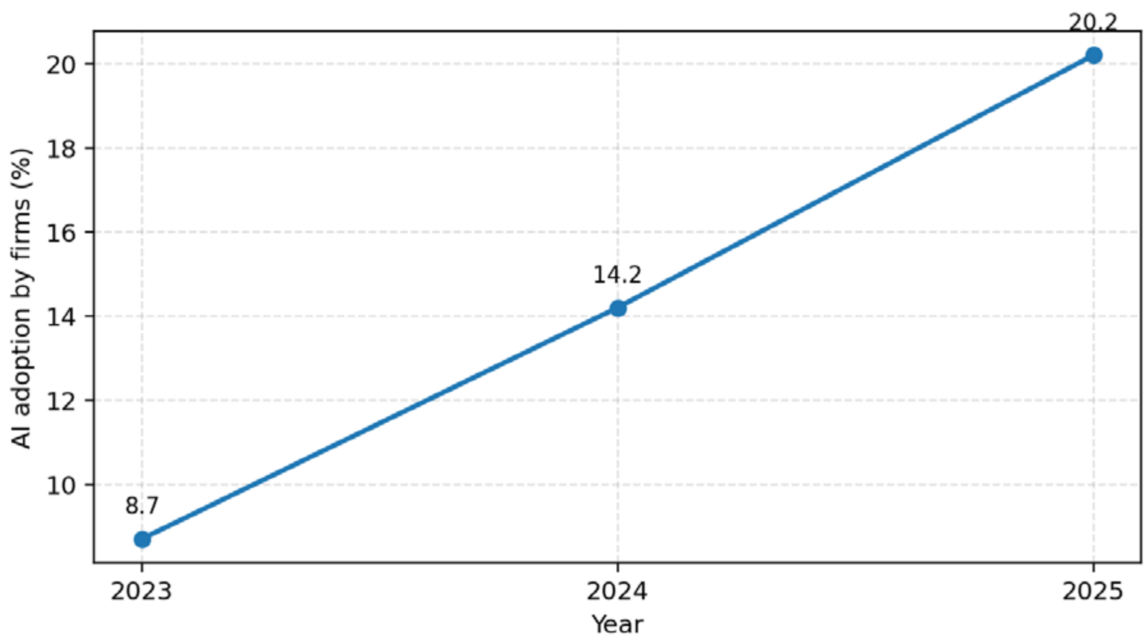

Figure1. O CDEGD firm-level AI adoption trend

As shown in Table 1, the world's leading smart cities in 2024 were mainly concentrated in Europe and Asia, with cities such as Zurich, Oslo, and Geneva consistently ranking among the top. A high-level smart city is not simply about a comprehensive balance of technology-intensive digital infrastructure, public service provision, institutional coordination, and resident perception. For Chinese cities, this distribution pattern necessitates that smart city construction prioritizes governance quality and application results, rather than merely focusing on the amount of equipment invested or the number of platforms built.

As shown in Figure 1, the adoption rate of artificial intelligence (AI) by companies in OECD countries has been increasing year by year, and has doubled in the last two years. This indicates that AI has transformed from an experimental technology to one that can be used on a large scale. The increased technological maturity of enterprises in smart city construction will directly impact the supply capacity of solutions proposed by city platforms, operators, and public sectors, thereby providing a more mature and complete industrial environment for the intelligent upgrading of urban transportation, energy, and security scenarios.

Table 2. OECD AI adoption by firms

Year	Adoption rate (%)	YoY growth (%)	Observation
2023	8.7	-	Early diffusion
2024	14.2	63.2	Rapid scaling
2025	20.2	42.4	Broad deployment

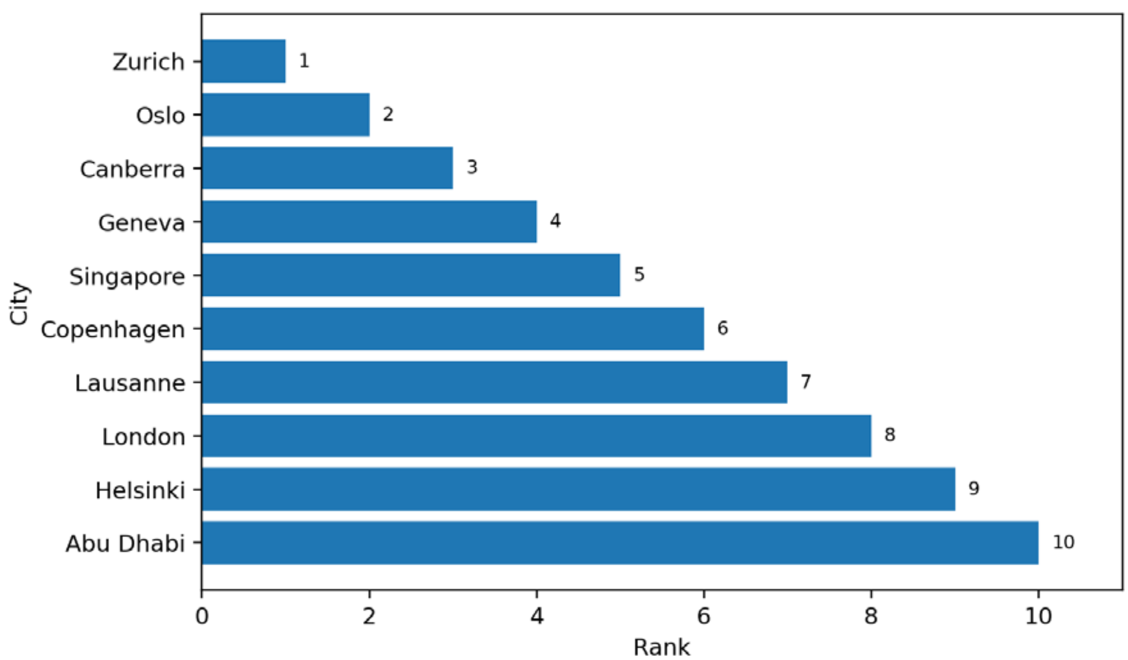

Figure 2. Top 10 cities in IMD Smart City Index 2024

Note: Table 2 further quantifies the growth rate of AI adoption. The significant increase in 2024 compared to 2023 indicates rapid internal dissemination of generative AI and automated analysis tools due to their widespread adoption. While the growth rate slowed in 2025, the overall adoption rate continued to rise, suggesting that AI is transitioning from new trials to routine deployment. Therefore, if urban governance departments prepare data interfaces, computing resources, and operations and maintenance in advance, they can effectively support future technological demands.Note: Figure 2 shows the ranking structure of the top ten cities in the IMD Smart City Index 2024. As can be seen from the table, European cities make up the largest number of the top ten, indicating that smart city competitiveness is more about advantages in institutional accumulation, governance collaboration, and digital public service experience, rather than individual technological leadership. The inclusion of Singapore, Abu Dhabi, and other countries in the top ten also demonstrates the strong catching-up capabilities of Asia and the Middle East in high-intensity infrastructure construction and platform governance, providing valuable comparative examples for my country's smart city development.

3. Raise questions

Although artificial intelligence has a broad prospect in the construction of smart cities, its application is not a straight line, but a difficult path full of twists and turns. First of all, there is a lack of data foundation and data sharing is also limited. Smart cities involve many departments such as public security, transportation, housing and construction, emergency response, environmental protection, urban management and energy. There are different data standards, collection frequencies, governance authority and data security levels among the systems owned by each department, which makes it difficult to form a unified data asset pool for training data. Dong et al. believe that issues such as open user privacy and ethical risk control have become current research hotspots [2]. Without a data foundation that can be tracked, governed and authorized, the algorithm system cannot obtain stable cross-scenario capabilities.

In addition, there is a contradiction between algorithm effectiveness and governance credibility. The public sector is different from the enterprise scenario. It attaches more importance to fairness, interpretability, procedural justice and public acceptability when carrying out urban governance. Benny Rjab et al. believe that institutional resistance, organizational inertia, talent shortage and ethical doubt are the reasons for the various difficulties in using AI in the construction of smart cities[1]. When algorithmic bias occurs in traffic law enforcement, risk warning and resource allocation, the differential impact or new governance unfairness will be more serious. Bosco et al. proposed that AI plus smart city projects should establish an ethical evaluation system for the entire life cycle in order to achieve the goal of human-centered and sustainable governance[7].

Furthermore, there is a phenomenon of "single-point optimization and overall imbalance" between scenarios. Currently, many urban projects focus on a single task, such as single-intersection signal optimization, single-park energy consumption management, or single-department video early warning, without cross-departmental collaboration or system-level evaluation. The research by dos Santos et al. shows that perceived benefits and trust levels affect the willingness to use AI smart city systems, but also affect adoption behavior [8]. Therefore, if urban projects only focus on the accuracy of technology and ignore user experience, institutional coordination, and citizen trust, a situation will arise where the technology is available but governance is difficult to implement.

Finally, there are the operating costs and long-term maintenance and management. High-frequency video access, continuous model updates, edge device upgrades, computing power allocation, and security protection all require long-term financial and organizational investment. Especially in medium-sized cities, without a phased implementation path, it's easy to see a lot of initial construction hype followed by weak later maintenance capabilities. Therefore, the key to AI-enabled smart cities is not "whether there are algorithms," but whether algorithms can be embedded into urban governance in an institutionalized way.

4. Problem Solving/Strategies

This article argues that the application of artificial intelligence in smart cities should shift from a technology import logic to a governance embedding logic, creating a systematic approach that includes a layered data governance system, scenario-based model planning, a closed-loop trust assessment system, and multi-stakeholder collaboration. First, regarding data, a cross-departmental data catalog, unified metadata standards, hierarchical access control, and privacy anonymization processes should be established to transform urban data from scattered resources into usable assets. Second, regarding models, different model paths such as prediction, optimization, identification, and anomaly detection should be selected based on different scenarios, including transportation, energy, and public safety, avoiding neglecting any single path in the pursuit of comprehensiveness. Third, from a governance perspective, a complete chain of model training, deployment, monitoring, auditing, and updates should be established to ensure that algorithm outputs can be monitored, explained, and corrected. Fourth, organizationally, a collaborative governance structure involving the government, platform enterprises, research institutions, and the public should be established to enhance the social acceptance of the project.

Starting from the actual traffic management environment, use time series prediction model to evaluate road network pressure, combine reinforcement learning to optimize signal timing, focus on some places to use digital twins for deduction and trial and error, and compare the impact of various different allocation methods. Urban energy scenarios should take load forecasting and demand response as the main axis, so that there is data connection between public building groups, park energy stations and distributed energy storage systems, so as to achieve the purpose of jointly controlling peak-valley difference, load change and equipment anomaly. Public safety scenarios should form a closed loop including identification, early warning, disposal and review, and use visual recognition, spatiotemporal modeling and rule review to prevent high-risk decisions from being made by relying solely on black box models. The development of urban artificial intelligence should not be regarded as a superposition of several isolated applications, but should become a strategic coupling between urban systems and artificial intelligence systems [9].

Smart city projects should not be measured by accuracy, recall or average error, but should create a comprehensive evaluation system that includes efficiency, resilience, fairness, energy consumption and public perception. In order to improve the enforceability of policies, the promotion can be divided into three stages: the initial stage is to create mature data scenarios and verifiable demonstration applications; the extension stage is to build cross-departmental platforms and rule interfaces to achieve multi-party cooperation; and the deepening stage is to add digital twins, generative AI and multi-agent collaboration to the city's decision support system to shape a complete capability from real-time operation to strategic planning. Phothong et al. believe that AI is only considered to have vitality when it can obtain sustainable symbiotic results at the citizen level through trust, adaptation and participation [10]. Therefore, the value of smart cities is not achieved by stacking technologies, but by seeking urban intelligence in a credible, transparent and collaborative way.

Based on the above ideas, five operational models are proposed to describe the main logic of smart city AI systems in application. First, the overall smart utility of a city can be viewed as a weighted sum of multiple performance indicators. Second, the congestion mitigation rate in traffic management measures the change in effectiveness before and after a strategy. In urban energy scenarios, total energy consumption is the result of time-of-use power accumulation. Anomaly scoring in public safety should include spatiotemporal, semantic, and behavioral characteristics. The city-level optimization goal is to find the optimal balance between service efficiency, operating costs, and governance risks. The relevant formulas are as follows:

$$U = \Sigma(w\_i\ x\_i),\ \ \Sigma w\_i = 1 \tag{1}$$

$$C\_r = (T\_0 - T\_1) / T\_0 \times 100\% \tag{2}$$

$$E\_s = \Sigma(P\_t\ \Delta t) \tag{3}$$

$$A\_s = \lambda\_1\ f(time) + \lambda\_2\ g(space) + \lambda\_3\ h(behavior) \tag{4}$$

$$J = \min \Sigma(aL\_t + bK\_t + cR\_t) \tag{5}$$

Equation (1) represents the comprehensive smart utility of the city. The indicators such as traffic efficiency, energy consumption intensity, risk response, and public satisfaction are all denoted as x_i, and the weight is w_i. Equation (2) represents the congestion relief rate after the implementation of the traffic governance strategy. Equation (3) represents the total energy consumption of the city's energy system in a certain period of time. Equation (4) represents the city-level joint optimization target. L_t is the service delay, K_t is the operating cost, and R_t is the governance risk.

Table 3 Scenario-based AI strategy matrix

Scenario	Core AI method	Primary target	Governance risk	Key reference
Traffic control	Prediction + RL	Delay reduction	Bias in signal priority	[4][8]
Urban energy	Load forecasting	Peak shaving	Model drift	[6][9]
Public safety	Vision + anomaly detection	Early warning	Privacy intrusion	[1][7]
Urban planning	Digital twin + simulation	Policy testing	Opaque assumptions	[3][6]
Citizen services	GenAI assistant	Service response	Trust deficit	[7][10]

This paper summarizes the technical approaches and governance risks of AI applications in smart cities from a scenario perspective. It concludes that the algorithmic goals differ across scenarios: traffic prioritizes real-time optimization, energy emphasizes prediction and scheduling, public safety prioritizes identification and early warning, planning prioritizes simulation and evaluation, and citizen services prioritize response quality and trust building. Therefore, when promoting AI projects in cities, a holistic design approach considering scenarios, goals, and risks is crucial; the same algorithm cannot be applied to all governance tasks.

5. Conclusion

Therefore, artificial intelligence is rapidly transforming smart city construction from digital management to intelligent governance. Its application focus has shifted from initial simple information collection and partially automated operations to comprehensive decision support encompassing traffic management, urban energy, public safety, and strategic simulations. Research over the past three years shows that AI has the potential to improve urban operational efficiency, enhance system resilience, and improve public services. However, whether this potential can translate into tangible performance depends on many factors, including data resources, institutional arrangements, algorithm credibility, and public participation.

Therefore, future smart cities cannot merely be demonstrations of single technologies. They should establish long-term, stable, and auditable mechanisms for the application of artificial intelligence within the urban governance system. This involves ensuring credibility through data governance, scenario application, ethical review, and performance evaluation, and achieving collaboration among multiple stakeholders to achieve sustainable development. Only when artificial intelligence is truly integrated into public governance processes and serves goals such as people, urban resilience, and sustainable development will smart city construction transform from "technologically advanced" to "effectively governed."

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