

## EFFICIENCY INDICATORS OF PUBLIC TRANSPORT AS A TOOL SUPPORTING SMART CITY DEVELOPMENT

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**Purpose:** To conceptualize AI-based algorithmic governance in smart cities as a multi-layer system linking urban data, AI models, and governance structures, and to propose a QoL-oriented evaluation framework for assessing its impact on citizens' quality of life.

**Design/methodology/approach:** The study adopts a conceptual, framework-development approach, building an integrated analytical framework and proposing the QoL-Algorithmic Governance Indicator System (QAGIS) for evaluating AI governance in smart cities.

**Findings:** The study shows that AI can improve QoL-oriented urban governance by increasing the relevance, accuracy, and consistency of governance actions, but only when algorithmic governance is integrated with existing governance structures and supported by explainable, transparent, and accountable AI mechanisms.

**Originality/value:** The article contributes by introducing the QAGIS framework for evaluating AI governance through both objective and subjective QoL dimensions and by clarifying the distinction between Smart City Governance and AI Governance, treating AI Governance as a necessary subsystem of responsible smart city governance.

**Keywords:** Artificial Intelligence, Algorithmic Governance, Quality of Life.

**Category of the paper:** Research paper.

### 1. Introduction

The increasing integration of Artificial Intelligence (AI) into smart city infrastructural environments is gradually transforming how cities are administered, governed, and assessed. The increasing instrumentalization of cities through sensing technologies, smart platforms, and a comprehensive data environment means that decision-making at the city level is now not limited to traditional administrative processes or occasional statutory reporting (Gil et al., 2026;

Rehman, 2026; Theocharis, Tsihrintzis, 2026). Rather, cities now increasingly depend on analytics models and decision-support algorithms that leverage data analysis and predictive capabilities in order to rationalize public services and manage increasingly complex socio-technical relationships. Here, the idea of 'algorithmic governance' has assumed significance as an interpretative tool in understanding how AI-related technologies can shape decision-making on public matters, effectively changing how citizens interact with institutions of governance (Ragab et al., 2025; Salhi et al., 2025; Tamtam et al., 2025; Jayanthiet al., 2025).

Regarding the governance aspects of decision support systems powered by artificial intelligence, there is a notable operational benefit provided. It can help achieve higher precision and real-time response of interventions in administrative matters, achieve a certain level of stability in decision-making activities, and optimize the use of resources in the most important sectors of smart city management, including transport, energy, the environment, and the digital government. This is particularly important when a strategic focus of a smart city is the improvement of the quality of living in the city. The growing presence of artificial intelligence in decision-making processes creates fundamental challenges in governance. This may increase the level of decision-making ambiguity and decrease the objectivity of administrative decision-making processes. Thus, the effectiveness of decision-making in the field of artificial intelligence powered governance cannot be judged solely upon the basis of decision-making effectiveness (El Moussaoui et al., 2025; Xiang, 2025; Shah et al., 2025; Skotnicka-Zasadzień, Wolniak, 2026; Wolniak et al., 2024a, 2024b).

The challenges listed in this section are overcome in this paper with an integrated framework that conceptualizes the multi-layered structure between (i) urban data systems, (ii) AI systems and analytics, and (iii) institutional governance frameworks. The framework helps in assessing AI outcomes across objective urban performance metrics, as well as across dimensions that are relevant to aspects of QoL, such as those based on citizens' perceptions. Specifically, methodological and ethical aspects surrounding AI systems used in the public domain, that is, transparency, bias, model ability, and interpretability, would receive special attention in the framework, and their implications for the correctness and validity of AI systems in governing would be explored. The main point that this paper would like to make is that AI can be useful in QoL-oriented urban governance by bringing about relevance, accuracy, and cohesion between governance actions; however, this is not possible without integrating algorithms with pre-existing governance frameworks and incorporating mechanisms like "explanation-oriented AI systems" that would help in understanding, auditing, and trusting AI systems.

We formulated two goals in this paper:

1. G1 - To conceptualize AI-based algorithmic governance in smart cities as a multi-layer system linking data, AI models, and governance structures.
2. G2 - To propose a QoL-oriented evaluation framework (QAGIS) for measuring how AI governance affects citizens' quality of life without undermining accountability and trust.

## 2. Conceptual Foundations

The smart city has developed from being essentially a technological vision, emphasizing information and communication technology infrastructure, sensors, and digital service provision, to encompassing an increasingly socio-technological and governance-focused approach. Today, the studies on smart cities increasingly take into consideration that urban “smartness” not only depends on the number of digital devices but on the capacity to convert data into public value. In this context, it has increased the relevance of governance frameworks because cities need to integrate different actors in the urban space, from government institutions and private providers to citizens and civil society organizations, and manage different goals from efficiency, sustainability, equity, to resilience (Derbas et al., 2026; Ali et al., 2025; Wang et al., 2025). The urban governance has developed from hierarchical administrative systems toward new governance frameworks focused on network-oriented systems that include distributed decision-making processes with increased use of policy instruments based on scientific knowledge. In this context, urban governance is increasingly informed by data streams and digital infrastructure and provides frameworks for the impact of algorithms in strategic and priority domains and in operational service delivery (Hamza, Ilyas, 2026; Zhang, Deng, 2025; Rosak-Szyrocka, Wolniak, 2025; Wolniak, Turoń, 2025). A possible conceptualization of algorithmic governance is the deliberate integration of computational models and algorithms with AI and decision rules based on data into the structures of public governance. This is not merely the automation of governance, but rather the metamorphosis of the very process of governance itself as guided by the output of algorithms (Zhuang, 2025; Lukić et al., 2025; Varghese, 2025; Voutyrakou, Skordoulis, 2025; Escudero et al., 2025). Thus, algorithmic governance can be considered to be multi-layered, consisting of city data environments (data collection, integration, and governance), the analytical side (AI and statistical models), and the governance side itself (authority and accountability).

Typologies of AI-governed governance generally distinguish between degrees of involvement of algorithms in the decision-making process: (i) advice systems assisting decision-makers; (ii) semi-automated governance systems implementing actions within specific boundaries; and (iii) autonomous governance systems operating under limited human control. There is another important distinction regarding the object of governance as a whole (Anastasopoulou, 2025; Kusumasari, Yahya, 2025; Ambroselli, 2025; Sullivan, 2025; Rosak-Szyrocka, Wolniak, 2025; Wolniak, Turoń, 2025). So, the scope of algorithmic governance may encompass decision-making at the level of micro-decisions (for instance, traffic management at intersections) as well as at the macro-level of policy choices (priorities in regional spatial planning, eligibility for social services). Lastly, the procedures of decision-making through algorithms may generally be transparent (with traceable rules and model operability), as opposed to “black box” machine learning methods.

Quality of Life is a paramount normative target of smart city initiatives. However, QoL is a very challenging topic in regard to conceptual definitions and methods used for its measurement. Speaking generally, QoL in the context of urban studies can be assessed using a combination of two approaches—the objective and the subjective one. Speaking specifically, the objective QoL measures involve the use of quantitative methods of study of city performance variables (Wijayasinghe, Sachitra, 2025; Padrón Nápoles et al., 2025; Huang et al., 2025; Jonek-Kowalska, Wolniak, 2025; Skubis et al., 2024; Jonek-Kowalska, Wolniak, 2023). This might concern air quality, noise level, traveling time, housing conditions, accessibility of healthcare and educational services, energy saving rates, crime rates, and the level of digital services. On the other hand, the subjective QoL research is focused primarily upon the citizen's living experience. This might include perceptions of citizen wellbeing, citizen satisfaction with public services of the city, trust of the public in city administrations as well as perceptions of balance and safety (Sverstiuk et al., 2025; Rondón-Duarte, Largacha-Martínez, 2025). The measurement of QOL in urban settings is fraught with several challenges. First, QOL is inherently multicriteria, and trade-offs between different goals are necessary; what enhances efficiency in traffic flow management could impair equity in-redistribution of congestions. Second, objective measurement could disregard local diversity and individualization. In objective measurement, an average-based governance policy could be inadequate since it ignores the needs of the minority. Moreover, objective measurement does not capture individuality in local settings. Objective measurement could be less useful because it is not sensitive to local conditions and local census. Subjective measurement could be useful because it is sensitive to local conditions. However, it could be less reliable because it could adapt to low quality. Subjective measurement could be useful because citizens could compare services with their expectancies. There could be risks in integrating QOL measurement in algorithmic governance (Davutoğlu, 2025; Liu, 2025; Jalal-Eddeen, 2025; Bax, 2025; de Castro, 2025).

### **3. AI-based analytics and decision-support systems to improve the quality of life (QoL)**

Decision Support Systems (DSS), leveraging AI technology, support real-time and predictive governance. They can detect potential urban risks, forecast public service demand, dynamically assign resources, and minimize the variation in the delivery of services. However, the relationship of DSS with QOL is not straightforward; it manifests at a different stage through intermediate variables like enhanced service provision, less exposure to the stressors of the urban environment (noise, pollution, and environmentally unsafe areas), and increased

incorporation of citizens' needs in the decision-making cycle of the governance process. As such, the improvement of QoL can be framed as follows:

AI systems impact QoL in several specific ways that can be operationalized:

a. Predictive governance and prevention.

AI models detect weak signals of congestion, pollution spikes, infrastructure failure, or safety risks. Preventive interventions reduce disruptions that impact QoL through stability and reliability of services.

b. Resource optimization and service accessibility.

Allocation models enhance the scheduling of public transport, energy balancing, deployment of emergency responses, and maintenance planning. QoL improves when these services become more accessible in time and space.

c. Personalization and citizen-centric service delivery.

AI can segment citizen needs—for example, elderly mobility patterns, disability accessibility requirements—and allow differentiated policy instruments. This may raise perceived relevance and satisfaction but also raises fairness and bias risks.

d. Management of the urban environment.

AI-based environmental monitoring facilitates decisions pertaining to green spaces, emission control, waste logistics, and noise regulation. These improvements will affect QoL through health, comfort, and perceived livability.

e. Digital governance and trust.

AI-enhanced platforms will improve both citizen contact channels and administrative effectiveness. On the other hand, such algorithmic opacity undermines trust in the government. Hence, QoL is dependent on legitimacy and governance transparency.

AI-based governance requires an evaluation logic that goes beyond operational efficiency and technical functionality. Many smart city programs still rely on narrow performance dashboards focusing on service outputs (e.g., response time, punctuality, throughput), which can create a misleading impression of success. In reality, algorithmic governance should be assessed as an intervention in a socio-technical system: it modifies decision processes, reshapes service allocation, and affects citizen perceptions of fairness and legitimacy. For this reason, the proposed QoL-Algorithmic Governance Indicator System (QAGIS) adopts a layered structure that captures the full chain from baseline urban conditions, through AI model quality and governance outputs, to objective and subjective QoL outcomes. The conceptual advantage of this architecture is that it prevents “output-only” evaluation and forces analysts to track whether AI-driven decisions actually improve human wellbeing and remain socially acceptable.

The first layer consists of Urban Condition Indicators and represents the pre-intervention context in which AI-based governance is operating. These metrics describe exposure conditions and service accessibility that shape QoL independently of any particular governance tool. Typical indicators include air pollution levels (PM<sub>2.5</sub>, NO<sub>2</sub>, O<sub>3</sub>), day/night noise exposure, urban heat stress days, travel time to key services, and safety environment proxies such as

incident density in public space. This layer methodologically plays the role of a baseline covariate set: it controls for the differences in initial conditions across the districts, enabling robust longitudinal comparisons. Without such a baseline layer, improvements attributed to AI may actually reflect exogenous variation rather than the governance impact of weather, seasonal tourism, or macroeconomic fluctuations.

The second level, AI System Performance Indicators, assesses the quality of models deployed in governance. This is an important task because algorithmic models have the ability to be very confident in their results, whether these models' predictions have any genuine, stable validity or not. The metrics that fall under this level include Forecast Accuracy (RMSE/MAE), Classifier Performance (F1/AUC), robustness to data drift, completeness of set coverage, and explainability properties (such as SHAP coverage, rule set availability). In addition to typical ML metrics, governance-relevant metrics, which include its traceability (logging, traceability of decisions) and fairness diagnostics (statistical parity, disparate impact approximations) measures, have to be incorporated. The purpose of this level of governance metrics is to ensure that all decisions made by governance, through the use of AI, have some technical soundness, which can be evaluated, argued against, or optimized through monitoring.

The third layer is “Governance Output Indicators,” which seeks to address the operational effectiveness of decision support through AI. The items within this layer regard changes in the level of service delivered within the smart city domains of mobility (congestion index, reliability of travel times, punctuality), energy (frequency of outages, effectiveness of demand response, losses reduced), environment (response time for incidents, reliability of waste collection), digital governance (completion rate of services, processing speed, complaint resolution), and public safety (response time for emergencies, rate of mitigation in risk hotspots). What is important is the fact that this layer does not currently quantify QoL itself, instead focusing on the outputs of governance as the alleged key drivers of QoL changes. It essentially acts as the linkage between the technical validity of AI and social outputs in the sense that it essentially tracks whether “AI does anything at all to the output of governance as opposed to being a ‘symbolic’ or ‘pilot only’ phenomena”.

The fourth and fifth layers focus specifically on QoL outcomes, distinguishing objective QoL outcome changes from subjective legitimacy and perception. The Objective QoL Outcome Indicators (Layer 4) measure the objective, tangible, and well-being-outcome-related impact, including exposure-normalized pollution load (PM2.5, population-normalized), health proxy variables (number of heat-related incidents, respiratory hospitalizations where available), walkability metrics, time poverty (lost hours due to commuting time and waiting time in queues), and equity of access to services (dispersion/Gini coefficient metrics). Finally, Subjective QoL and Legitimacy Indicators (Layer 5) aim to measure subjective, experiential, citizen-perceived values via survey research, crowd-sensing initiatives, or other participative means, including service satisfaction, sense of justice/fairness, trust in digital governance, trust in the transparency of AI governance decisions, sense of voice, and trust in

cybersecurity/privacy. The motivation to distinguish these layers stems from the fact that, through algorithmic governance, it can improve objective performance simultaneously with decreased subjective perception (for example, due to non-transparent decisions). Success in QAGIS means the achievement of convergence between objective QoL improvements and legitimacy, which makes it possible to assess whether it is practical to sustain and adapt these new AI governance projects in real-world urban settings.

Table 1 presents the proposed QoL-Algorithmic Governance Indicator System (QAGIS) as a structured framework for evaluating AI-based governance in smart cities through five complementary layers. The table operationalizes the logic that QoL impacts cannot be credibly inferred from service outputs alone, because AI interventions influence both technical decision processes and social legitimacy conditions.

**Table 1.**  
*A QoL-Oriented Indicator Concept for AI Governance*

Layer	Indicator	Unit	Data Source	Frequency	Interpretation/Role
Layer 1: Urban Conditions (Baseline Exposure)	Air quality (PM2.5, NO <sub>2</sub> , O <sub>3</sub> )	µg/m	Environmental sensors, national monitoring	Hourly/ Daily	Population-weighted exposure index
Layer 1: Urban Conditions (Baseline Exposure)	Noise exposure	dB(A)	Noise sensors / GIS modelling	Daily/ Monthly	Day-night exposure differentiation
Layer 1: Urban Conditions (Baseline Exposure)	Accessibility to key services	Minutes	GIS + transport network data	Monthly/ Quarterly	Average travel time to healthcare, education, hubs
Layer 2: AI System Performance (Model Quality)	Predictive accuracy (forecasting)	RMSE/ MAE	Model validation logs	Per model update	Technical validity of prediction outputs
Layer 2: AI System Performance (Model Quality)	Classification performance	F1/AUC	Model validation logs	Per model update	Robustness in event classification
Layer 2: AI System Performance (Model Quality)	Model drift stability	% change	Monitoring pipeline	Weekly/ Monthly	Detects degradation over time
Layer 2: AI System Performance (Model Quality)	Explainability coverage	% interpretable outputs	XAI tools (SHAP/LIME)	Per model update	Degree of transparency for oversight
Layer 2: AI System Performance (Model Quality)	Bias/fairness diagnostics	Parity ratio/ DI	Bias audit reports	Quarterly	Measures distributional harms
Layer 3: Governance Outputs (Service Delivery KPIs)	Mobility reliability	% punctuality	Transport operations data	Daily/ Weekly	Travel time predictability and punctuality

Cont. table 1.

Layer 3: Governance Outputs (Service Delivery KPIs)	Energy outage frequency	Events/ year	Utility grid logs	Monthly/ Yearly	Infrastructure resilience indicator
Layer 3: Governance Outputs (Service Delivery KPIs)	Environmental incident response time	Minutes	City management system	Per event	Speed of reaction to pollution spikes
Layer 3: Governance Outputs (Service Delivery KPIs)	Digital service completion rate	% successful trans- actions	E-government platform logs	Monthly	Administrative efficiency indicator
Layer 4: Objective QoL Outcomes	Exposure- adjusted pollution burden	Index	Sensor data + population maps	Monthly/ Quarterly	Captures health- relevant exposure
Layer 4: Objective QoL Outcomes	Time poverty (commuting + queues)	Hours/ month	Transport logs + surveys	Quarterly	QoL loss via wasted time
Layer 4: Objective QoL Outcomes	Spatial equity of service availability	Gini/ Dispersion index	Service registry + GIS	Yearly	Measures fairness across districts
Layer 5: Subjective QoL & Legitimacy	Citizen satisfaction with services	Likert scale	Citizen surveys/app feedback	Quarterly/ Semiannual	Perceived QoL improvement
Layer 5: Subjective QoL & Legitimacy	Trust in AI- supported governance	Likert scale	Citizen panels/surveys	Semiannual	Legitimacy and acceptance measure
Layer 5: Subjective QoL & Legitimacy	Perceived transparency of decisions	Likert scale	Citizen surveys	Semiannual	Signals explainability effectiveness
Layer 5: Subjective QoL & Legitimacy	Perceived fairness/inclusio n	Likert scale	Citizen surveys	Semiannual	Captures risk of marginalization

Source: Own study.

A QoL-oriented AI governance system should be conceptualized as a cyclical evaluation architecture rather than a one-time implementation of algorithms and dashboards. The fundamental reason is that cities are dynamic socio-technical systems: exposure conditions, mobility patterns, service demand, and citizen expectations change over time, which means that any AI model embedded in governance will inevitably face instability, drift, and shifting contextual constraints. The evaluation cycle begins with baseline mapping (Layer 1) to establish the initial state of urban conditions and service accessibility, followed by model and data validation (Layer 2) to confirm that AI systems are technically reliable, explainable, auditable, and fair before they influence public decisions. Without these first stages, later outcome improvements cannot be causally attributed to AI governance, and governance actors may mistake short-term correlations for genuine improvements.

The cycle then progresses to the operational level via operational monitoring (Layer 3), whereby the actual output effects of AI-driven governance on key service domains (transport, energy, environment, digital) are ascertained. Nevertheless, mere operational optimization does not represent a sufficient condition for AI-driven governance by itself. Thus, the subsequent

layers centre on collective, social-level results: QoL outcome evaluation (Layer 4), whereby modifications pertaining to concrete living circumstances (pollution load, time poverty, geographic distribution, health-related proxies) are ascertained, together with the quantification of subjective perceptions like satisfaction, fairness, transparency, and confidence regarding protection, via legitimacy and trust evaluation (Layer 5). This two-faceted outcome assessment has particular theoretical importance, as algorithmic governance may translate into improved technical efficiency on the one hand, but, on the other, culminate in social opposition if, for instance, the system is perceived as opaque, unjust, or unaccountable by the citizenry.

The evaluation model must include a structured feedback loop in which evidence from all layers triggers recalibration of models, redefinition of governance priorities, and systematic policy learning. In practice, this means updating datasets, adjusting model parameters or replacing models when drift is detected, redesigning decision rules to improve equity, and revising QoL targets based on citizen feedback. While this cyclical architecture aligns with theories of evidence-based governance and continuous improvement, it contributes an often-missing dimension: algorithmic legitimacy. Here, legitimacy is treated not as a normative slogan but as an indicator-driven condition for sustainability—meaning that AI governance is considered viable only if it remains transparent, contestable, and trusted over time, alongside measurable improvements in objective QoL outcomes (table 2).

**Table 2.**  
*Cyclical Evaluation Architecture for QoL-Oriented AI Governance*

Cyclical stage/ element	Purpose and evaluation focus
Principle: cyclical architecture (not one-time deployment)	AI governance must be evaluated continuously because cities are dynamic socio-technical systems; exposure conditions, demand, mobility patterns and citizen expectations change, causing model instability and concept drift.
Layer 1: Baseline mapping (urban conditions)	Establish the initial state of the city (environmental exposure, accessibility, safety context) as baseline covariates enabling longitudinal comparison; prevents misleading attribution of changes to AI interventions.
Layer 2: Model and data validation (AI system quality)	Verify that AI models are technically and procedurally fit for governance: reliability, explainability, auditability, fairness, data completeness; ensures AI does not enter decision-making without methodological legitimacy.
Layer 3: Operational monitoring (governance outputs)	Track the measurable outputs of AI-supported governance in service sectors (mobility, energy, environment, digital services); demonstrates whether AI influences real operational performance, not only “pilot metrics”.
Layer 4: Objective QoL outcome evaluation	Quantify tangible QoL outcomes causally linked to governance outputs (pollution burden, time poverty, spatial equity, health proxies); shifts evaluation from efficiency to citizen living conditions.
Layer 5: Subjective QoL and legitimacy assessment	Measure citizen perceptions (satisfaction, fairness, transparency, privacy confidence, trust); captures legitimacy constraints, since objective improvements may still trigger resistance if governance is perceived as biased or opaque.
Feedback loop: recalibration and policy learning	Evidence from all layers triggers updates: dataset refresh, model tuning/replacement under drift, redesign of decision rules (incl. equity constraints), QoL target adjustment via citizen feedback; operationalizes continuous improvement in AI governance.
Algorithmic legitimacy as a sustainability condition	Legitimacy is treated as an indicator-based requirement (not a philosophical add-on): AI governance is viable only when it remains transparent, contestable, trusted over time, and yields measurable QoL gains.

Source: Own study.

The article employs a comparative analysis methodology to evaluate business analytics educational programs in bachelor's and engineering degrees across selected Polish universities. This method was chosen because it enables a systematic examination of differences and similarities in curricula and their alignment with labour market demands. Moreover, it facilitates identifying trends, strengths, and weaknesses in educational approaches to prepare business analysts. This approach is consistent with the article's goal of examining how educational offerings match market needs.

The data sources were the syllabi from official university websites and course catalogues. These are primary sources of information, ensuring accuracy and relevance in the analysis of educational content. Each subject included in the study programmes was assigned skills that students could acquire by completing these courses. Since the study programs contain a huge number of subjects (several dozen), the research was narrowed down to subjects taught within the specializations related to data analysis.

Skills were grouped into four categories—analytical, technical, communication, and project management. This classification reflects the competencies expected of modern business analysts, as identified in industry reports and literature (e.g., PMI Guide to Business Analysis). It ensures the study's findings are directly applicable to workforce requirements. Five bachelor's degree programs and five engineering degree programs from leading Polish universities were selected for the analysis, including Silesian University of Technology, Warsaw School of Economics, University of Economics in Katowice, University of Szczecin, Adam Mickiewicz University in Poznań, Wrocław University of Science and Technology, Cracow University of Technology, Lodz University of Technology and Kielce University of Technology.

In addition, the analysis results were correlated with labour market data (e.g., wage reports and labour demand statistics). The source of this data were platforms such as wynagrodzenia.pl and Google Trends, as well as IT market reports. This ensures that the analysis is based on real-world relevance, linking education to industry.

#### **4. Smart City Governance vs AI Governance**

The difference between Smart City Governance and AI Governance is more than just semantic: rather, it corresponds to two different levels of analysis and two different objects for the governance (see table 3). In particular, Smart City Governance captures an umbrella term for the characterization of the coordination of cities in the presence of stakeholders, infrastructure, and public services in digitally enabled cities. It is thus primarily focused on the governance of the city as a sociotechnical system, in which technology is understood as an instrument which supports strategic objectives of efficiency, sustainability, resilience, and overall enhancement of citizens' quality of life. By contrast, AI Governance has primarily

been focused on the governance of AI systems themselves, and this encompasses issues like design choice, accountability, and risk management, without relation to the particular application domain of AI. This thus makes AI Governance more limited in scope but more detailed in technology and procedural terms, since AI Governance encompasses the entire life path of AI, from data governance in AI training up through auditing of AI system deployments (Abraham, 2025; Ottmann, 2025; Nieuwenhuizen, 2025). One of the major points of divergence relates to the governance target or the thing that is governed. Smart City Governance has the governance target as the delivery of urban services and the coordination of institutions related to transportation, energy, the environment, safety, digital administration, and engagement tools for the community. The role of AI, in this case, is only one of the enabling technologies for modernization in governance. AI Governance, with a focus on the algorithms, data, and decision pipelines, presents the governance target as the algorithms and data themselves and aims to create governance by defining the rules and control frameworks for making the outputs of AI more transparent, robust, reliable, and contestable. The importance of this viewpoint cannot be underestimated because the use of AI in smart city initiatives is increasing, and it is being used for prioritization and recommendations, which indirectly affects governance decisions (Sinha, Chopra, 2025; Hassan et al., 2024; Alakoum, Nica, 2024). The goals and performance logic of these governance concepts also differ. Smart City Governance evaluates success through service-level KPIs and QoL outcomes, including both objective indicators (e.g., pollution exposure, commuting times, service accessibility) and subjective assessments (e.g., citizen satisfaction and trust). AI Governance uses a different evaluation regime: model performance, drift stability, bias diagnostics, explainability coverage, and auditability. These metrics are not optional technical details; they constitute the conditions under which AI can be legitimately integrated into public governance. Thus, Smart City Governance answers whether the city functions effectively and inclusively, whereas AI Governance answers whether AI systems used in governance are controllable, reliable, and aligned with ethical and legal standards (Dash, 2024; Vella et al., 2025; Wolniak et al., 2025). Another distinction arises from the risk landscape. Smart City Governance is typically concerned with systemic urban risks such as infrastructure reliability, cyber threats, service disruptions, and inequalities in access to public goods. AI Governance focuses on algorithm-specific risks, including bias and discrimination, opacity (“black-box” decisions), automation bias in decision-making, dataset shift and concept drift, and the inability to attribute responsibility. These risks are qualitatively different because they can emerge even in high-performing service contexts. For example, a predictive policing or welfare allocation model may increase operational efficiency while simultaneously intensifying social inequality through biased training data, undermining legitimacy even if service KPIs appear improved (Varghese, 2025; Kusumasari, Yahya, 2025; Ambroselli, 2025).

The accountability structure further highlights the divergence. In Smart City Governance, accountability is generally institutional: elected officials, city departments, operators, and contractors can be held responsible through formal administrative and political procedures. In AI Governance, accountability becomes distributed and technically mediated. Responsibility may be shared among municipal authorities, AI vendors, data owners, model developers, and external auditors. This distribution complicates governance because it introduces gaps between decision authority and technical causality. In algorithmic systems, the “reason” for a decision may be embedded in complex model behavior rather than explicit administrative logic. Hence, AI Governance emphasizes traceability and audit trails precisely to reconstruct responsibility and enable contestability.

The relation between these concepts is best understood as a structural dependence: AI Governance often represents a requisite sub-system of Smart City Governance in cities that pursue algorithmic decision-support. A smart city may exist independently from comprehensive AI deployment-e.g., it may be focused on IoT monitoring and digital services-but it cannot responsibly deploy AI-based governance without AI Governance mechanisms. Hence, AI Governance represents the methodological and ethical infrastructure that enables algorithmic governance to become part of the general smart city governance framework without undermining transparency, accountability, or civic trust. In this sense, the table explains how Smart City Governance is directed toward the management of the city and its outcomes, while AI Governance is oriented toward the control of the technology that increasingly defines those outcomes.

**Table 3.**

*Distinction between Smart City Governance and AI Governance*

<b>Dimension</b>	<b>Smart City Governance</b>	<b>AI Governance</b>
Core focus	Governance of the city as a socio-technical system (public services, infrastructure, stakeholders) supported by digital technologies	Governance of AI technologies: design, deployment, monitoring, auditing, and accountability of AI systems
Scope	Broad: all urban domains (mobility, energy, environment, health, safety, planning, digital services)	Narrower and technology-focused: AI lifecycle (data → model → deployment → monitoring) across domains
Object of governance	Urban institutions and service ecosystems (public administration, PPPs, citizen participation)	AI models and decision systems (algorithms, datasets, risk controls, compliance mechanisms)
Primary goal	Improve service quality, efficiency, sustainability, resilience, and citizens' quality of life	Ensure safe, lawful, transparent, fair, and controllable use of AI while minimizing harms
Main drivers	Digital transformation, urbanization pressures, sustainability agendas, demand for better services	Rapid ML/AI diffusion, automation of decisions, opacity and bias risks, emerging AI regulation
Key mechanisms	Multi-stakeholder coordination, participatory governance, urban data platforms, performance dashboards	AI risk management, model auditing, explainable AI, fairness testing, drift monitoring, MLOps governance
Decision-making model	Institution-driven decisions increasingly informed by analytics and digital tools	Algorithm-influenced decisions (recommendations, predictions, scoring); potential semi-automation

Cont. table 3.

Typical instruments	Smart city strategies, service KPIs, policy programs, citizen engagement platforms, open data initiatives	AI policies, model/data documentation (model cards, datasheets), algorithmic impact assessments, audit trails
Ethical emphasis	Inclusion, equitable access to services, privacy in city platforms, legitimacy of public decisions	Fairness, non-discrimination, explainability, accountability, contestability, privacy-by-design
Data orientation	Open data, integrated city data ecosystems, IoT/sensor integration, interoperability	Data lineage, data quality and bias control, minimization, secure data pipelines, governance of training data
Performance evaluation	Urban service performance + QoL outcomes (objective indicators and subjective perceptions)	Technical and governance metrics: model performance, robustness, transparency, fairness, auditability
Risk landscape	Systemic urban risks: infrastructure failures, cyber risk, inequality, service disruption	Algorithmic risks: bias, black-box decisions, automation bias, drift, adversarial vulnerabilities
Accountability model	Institutional accountability (mayor/city council, departments, operators, contractors)	Distributed accountability: city authorities + vendors + data owners + model owners + auditors
Stakeholders	Citizens, NGOs, city departments, utility operators, private providers, academia	AI developers/engineers, data stewards, model owners, regulators, auditors, affected users
Outputs	Effective, adaptive, inclusive governance of urban services and development	Responsible AI deployment ensuring legitimacy, transparency, control, and prevention of social harms
Relationship between concepts	Umbrella concept structuring digital and service governance in cities	Typically a component/ subsystem within smart city governance, but can exist independently

Source: Own study.

## 5. Conclusion

This paper has explored the increasing use of Artificial Intelligence in the governance of smart cities by defining the use of AI in the governance of smart cities as an embedded governance system with quantifiable implications for society. The implications of this governor system were exemplified by the fact that the governance of smart cities can be defined as the integration of data environments, artificial intelligence analysis, and governance systems as mutually enabling technologies. This is an important definition because the focus of this issue is moved away from efficiency and towards the area of legitimacy.

The first objective of this paper (G1) was fulfilled by describing AI-driven algorithmic governance as a multi-layered system integrating (i) urban data ecosystems, (ii) AI models and decision-support analytics, and (iii) institutional structures of governance in general. By this multi-layered definition, it becomes clear that "AI in cities" is not only an operational optimization method, but it is mainly a socio-technical system of governance that affects not only how problems are defined, but how interventions should be treated as priorities, and how accountability may or may not be attained on a public governance level by applying this AI-driven socio-technical subsystem of governance in cities. By identifying advisory,

semi-autonomous, and fully autonomous dimensions of algorithmic interventions, and by indicating that governance outcomes depend on transparency, bias, and explainability characteristics of models, this paper offers a unified theoretical background on how this paradigm of governance should be understood, and not perceived as an add-on feature of governance at all.

The second goal (G2) was realized through the development of the QoL-oriented evaluation framework QAGIS, which operationalizes the causal chain from AI model quality to governance outputs and finally to citizen wellbeing. The framework explicitly avoids the methodological mistake of evaluating AI governance only through operational KPIs. Instead, QAGIS introduces a structured five-layer logic: baseline urban exposure conditions (Layer 1), AI system performance and procedural governance indicators (Layer 2), governance service outputs (Layer 3), objective QoL outcomes such as pollution burden, time poverty and spatial equity (Layer 4), and finally subjective QoL and legitimacy indicators including perceived fairness, transparency and trust (Layer 5). In this way, the paper establishes a measurable and audit-friendly structure for assessing whether AI governance actually improves quality of life without undermining accountability and public confidence.

A key implication of the proposed approach is that QoL-oriented algorithmic governance must be treated as a continuous cyclical evaluation architecture, not a one-time deployment of algorithms. Cities are dynamic systems characterized by demand shifts, mobility fluctuations, seasonal environmental variability, and evolving citizen expectations; therefore, AI models will inevitably face drift and contextual instability. The QAGIS logic supports governance learning through feedback loops: evidence from QoL outcomes and legitimacy indicators should trigger model recalibration, rule redesign, and policy adjustment. This interpretation positions legitimacy as a measurable sustainability condition: AI governance is viable only when it remains transparent, contestable, and trusted while delivering tangible QoL improvements.

This article advances smart city governance knowledge by shedding new light on the difference between Smart City Governance and AI Governance, thereby indicating that AI Governance needs to be a required subsystem whenever AI decision support has a strong impact on a particular smart city. Further smart city-related knowledge development may incorporate empirical evaluation, such as studying long-term effects on smart cities of deploying AI, as well as simulation tests regarding comprehensive indices like AI Governance Readiness, as well as building common data for comparison of smart cities.

The research has a conceptual nature, being framework-developing, hence it neither empirically verifies QAGIS in a real city setting nor investigates the causal effect of AI governance on QoL metrics. The indicator layers proposed are based on the underlying quality of the urban datasets, besides requiring effective monitoring systems, but the reality could be hindered by the presence of gaps in the data, lock-in effects, privacy restrictions, etc.

Future studies should empirically validate QAGIS in real smart-city deployments using longitudinal and quasi-experimental designs to identify causal QoL effects of AI-supported governance across sectors (mobility, energy, environment, digital services). Research should develop and test standardized measurement protocols for legitimacy-related indicators (trust, perceived fairness, perceived transparency) and investigate how these subjective constructs interact with objective QoL improvements under different levels of algorithmic autonomy.

## Acknowledgements

This paper was published as part of the statutory research ROZ 1: 13/010/BK\_26/0093 at the Silesian University of Technology, Faculty of Organization and Management.

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