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SMART CITIES IN THE AGE OF ARTIFICIAL INTELLIGENCE: TOWARDS DATA-DRIVEN URBAN MANAGEMENT

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Purpose: The purpose of this publication is to analyse the potential of data driven urban management.
Design/methodology/approach: Critical literature analysis. Analysis of international literature from main databases connecting with researched topic.
Findings: The findings indicate that AI-driven Smart Cities are not defined by individual technologies but by the degree of integration across layered digital infrastructures and data-driven management models. The evidence suggests a gradual shift from fragmented, sector-specific applications toward more interconnected and platform-based systems, where real-time data processing and predictive analytics enable adaptive urban governance. At the same time, this transformation remains uneven, as technological advancement is frequently constrained by data quality issues, institutional fragmentation, and unresolved challenges related to transparency, accountability, and system interoperability.
Originality/Value: Detailed analysis of all subjects related to the problems connected with the usage analysed scientific problem.
Keywords: Artificial intelligence; smart cities; data-driven urban management; urban sustainability; predictive analytics; digital infrastructure; data governance.
Category of the paper: literature review.

1. Introduction

The increasing incorporation of artificial intelligence into organizational settings has begun to reconfigure—rather than simply extend—the analytical foundations of management sciences. This is particularly visible in the domain of People Analytics, where the use of employee-related data is no longer limited to descriptive reporting but is progressively oriented toward predictive, behaviorally informed inference. Earlier forms of human resource analytics tended to rely on retrospective indicators—turnover rates, absenteeism, performance scores—

aggregated and interpreted after the fact. That logic now appears insufficient. Contemporary approaches move toward continuous, multi-source data processing, often integrating digital trace data, interaction patterns, and contextual variables. The objective shifts: from describing what has occurred to anticipating what might emerge. Not always cleanly (Alfaidi et al., 2026; Dey et al., 2026; Han, 2026).

This transformation reflects a broader epistemological reorientation within organizational research. Data-driven reasoning, supported by algorithmic models, increasingly supplements—or in some cases displaces—traditional hypothesis-driven approaches. Artificial intelligence, in this context, does not function merely as an auxiliary analytical instrument. It becomes embedded within the analytical architecture itself, shaping how problems are framed, how variables are selected, how relationships are inferred. The distinction between method and theory begins to blur. At least partially. Models detect patterns that are not always anticipated by existing theoretical frameworks, and this introduces both opportunity and tension.

The expansion of AI-driven People Analytics therefore raises a set of theoretical and methodological questions that are not easily resolved. The relationship between inductive pattern discovery and established theories of organizational behavior becomes less stable. Should models be guided by theory, or should theory adapt to model outputs? There is no straightforward answer. Additionally, the issue of contextual interpretation becomes more pronounced. Data extracted from organizational systems—emails, workflows, digital interactions—are inherently situated, shaped by culture, structure, informal norms. Without careful interpretation, algorithmic outputs risk becoming decontextualized abstractions.

The goal of this paper is to analyse the potential of data driven urban management.

2. Theoretical and Technological Foundations of AI-Driven Smart Cities

The concept of Smart Cities has not evolved in a linear or entirely coherent manner; rather, it has shifted—sometimes unevenly—from a predominantly infrastructure-oriented paradigm toward a more integrated configuration in which artificial intelligence (AI) operates as a coordinating, almost mediating layer. Earlier interpretations tended to equate "smartness" with the deployment of information and communication technologies (ICT), sensor arrays, and digital platforms designed to enhance operational efficiency. That framing, while technologically grounded, often privileged hardware and connectivity over systemic integration. Something was missing there. More recent perspectives, increasingly influenced by urban informatics and systems-oriented thinking, begin to treat the city as a complex adaptive system—loosely bounded, continuously evolving—where data streams, institutional logics, and behavioral patterns intersect in ways that are not always predictable. Within this reframed context, AI does not simply augment existing infrastructures; it alters the underlying logic of coordination itself, enabling forms of prediction, adaptation, and partial autonomy that were previously out of reach (Polydoros et al., 2026; Chawla et al., 2026; Masud et al., 2026; Dissanayake et al., 2026).

From a theoretical point of view, the incorporation of AI into urban systems resists explanation through any single framework. The Technology–Organization–Environment (TOE) perspective offers an initial structure, situating AI adoption at the intersection of technological maturity, organizational readiness, and external pressures—regulatory, societal, sometimes geopolitical. Yet, TOE remains somewhat descriptive. It captures conditions, less so dynamics. The Resource-Based View (RBV) extends the analysis by positioning data as a strategic asset and analytical capability as a differentiating factor in urban performance. Cities, in this sense, begin to resemble data ecosystems rather than purely administrative entities. Still, RBV has its own limits—it tends toward static equilibrium assumptions. This is where Dynamic Capabilities theory becomes analytically useful, emphasizing the capacity of urban institutions to reconfigure resources under conditions of uncertainty and rapid change. Not always smoothly. The combination of TOE, RBV, and Dynamic Capabilities does not produce a fully unified theory, but it does allow for a more layered interpretation—one that acknowledges both structure and motion in the embedding of AI within governance systems.

At the technological level, AI in Smart Cities functions as an upper-layer capability built upon a stratified digital architecture. At the base, the Internet of Things (IoT) provides the sensory substrate: distributed sensors embedded across transport networks, energy infrastructures, environmental monitoring systems, public utilities. These devices generate continuous streams of heterogeneous data, often noisy, sometimes incomplete. Transmission occurs through communication networks—frequently leveraging high-bandwidth solutions such as 5G—toward centralized or distributed data environments. The intermediate layer, where cloud and edge computing intersect, becomes critical here. It is not just about storage, but about latency, responsiveness, and control. Centralized processing offers scale; decentralized architectures provide resilience and, in some cases, greater alignment with data sovereignty requirements. The trade-offs are structural, not merely technical (Hussein et al., 2026; Dorostkar, 2026; Kumar et al., 2026; Rosak-Szyrocka, Wolniak, 2025b).

Above this infrastructural base, AI techniques—machine learning, deep learning, reinforcement learning—are deployed to extract patterns and inform decisions. Machine learning models are widely used for relatively well-defined tasks: traffic optimization, demand forecasting, anomaly detection. Deep learning extends analytical capacity into domains characterized by unstructured data—images, video streams, complex sensor outputs—enabling applications in surveillance, infrastructure diagnostics, public safety. Reinforcement learning remains less pervasive, but conceptually significant; it introduces adaptive control logics that evolve through interaction with dynamic environments. Not always stable, though. What becomes increasingly relevant is not the isolated use of these techniques, but their integration into decision-support systems that operate in near real time, sometimes with minimal human oversight.

This layered technological configuration supports what is often described as data-driven urban management. The shift, however, is not abrupt—it unfolds gradually, and not uniformly across domains. Decision-making moves away from periodic, retrospective evaluation based on aggregated indicators toward more continuous, forward-oriented optimization processes. Traffic flows are adjusted dynamically; energy systems respond to fluctuations in demand and supply; service allocation becomes, at least in principle, predictive. Yet this transformation introduces new dependencies. Data quality becomes a constraint. Model calibration matters more than is often acknowledged. Interoperability issues—between systems, between institutions—can generate friction that offsets potential efficiency gains. Sometimes the system works, but not quite as intended.

The human dimension complicates this picture further. While the technological narrative emphasizes efficiency, optimization, responsiveness, the social embedding of AI-driven systems remains uneven, occasionally fragmented. Human-centered approaches—often associated with the notion of "Smart City 3.0"—attempt to reintroduce balance by foregrounding participation, transparency, inclusivity. But tensions persist. Algorithmic decision-making, especially when based on opaque or highly complex models, raises questions of accountability and explainability. Who is responsible for a decision generated by a model? Can it be contested? Trust becomes an issue—not abstract, but operational. And not easily resolved (Daovisan, 2026; Orduño-Osuna et al., 2026; Jonek-Kowalska, Wolniak, 2021, 2023).

AI-driven Smart Cities should not be conceptualized as purely technological constructs. They are better understood as socio-technical configurations, shaped by the co-evolution of infrastructure, institutional arrangements, and human practices. Their effectiveness depends on more than computational capacity or data availability; it is contingent upon organizational learning processes, regulatory alignment, and cultural acceptance. Some urban systems achieve high levels of technological sophistication yet encounter resistance at the institutional or societal level. Others proceed more incrementally—slower, perhaps, but with greater alignment between technological deployment and social expectations. There is no single developmental trajectory. Instead, multiple pathways emerge, conditioned by local constraints, governance models, and strategic priorities. Not entirely predictable, and not easily standardized.

The table 1 presents a layered architecture of AI-driven Smart Cities, linking each technological stratum with its core components and corresponding system functions. It highlights the sequential yet interdependent nature of urban digital infrastructure, where data acquisition, transmission, processing, and analytics collectively enable adaptive and real-time urban management. At the same time, it underscores that technical performance is contingent upon supporting layers such as cybersecurity, governance frameworks, and user interaction mechanisms, which ensure system reliability and societal integration.

Table 1.
Technological Foundations of AI-Driven Smart Cities

Technological Layer	Core Technologies	Functions and System Role
Data Acquisition Layer	IoT sensors, cameras, GPS, mobile devices	Continuous collection of real-time, heterogeneous urban data; foundation for all higher-level analytics
Communication Infrastructure	5G networks, LPWAN, fiber-optic systems	High-speed, low-latency data transmission; enables real-time system responsiveness
Data Storage and Processing	Cloud computing, edge computing, data lakes	Scalable storage and distributed processing; balance between centralization and local responsiveness
Data Integration and Management	Urban data platforms, APIs, interoperability frameworks	Integration of heterogeneous datasets; supports cross-domain data exchange and system coordination
Artificial Intelligence and Analytics	Machine learning, deep learning, reinforcement learning	Pattern recognition, prediction, optimization, and adaptive control of urban systems
Simulation and Modeling	Digital twins, system dynamics models	Scenario analysis, forecasting, and virtual testing of urban policies and interventions
Decision Support Systems	AI-driven dashboards, optimization algorithms	Support for policy-making and operational decisions; transition toward semi-automated governance
Cybersecurity and Data Protection	Encryption, anomaly detection, blockchain	Protection of data integrity, privacy, and system resilience against cyber threats
User Interface and Interaction	Smart applications, dashboards, chatbots	Communication between systems and users; enables monitoring, control, and citizen engagement
Governance and Control Layer	Data governance frameworks, regulatory technologies (RegTech)	Ensures compliance, accountability, and ethical use of AI systems in urban environments

Source: Author's own work.

3. Applications of AI-Driven People Analytics in Understanding Organizational Behavior

The application of artificial intelligence within urban systems has not progressed in a strictly linear fashion; rather, it has expanded from relatively isolated, domain-specific deployments toward more integrated—though still imperfect—configurations in which multiple subsystems are connected through shared data infrastructures and analytical logics. This shift reflects something broader than simple technological upgrade. It signals a transition from digitization, understood as the conversion of analog processes into digital form, toward datafication, and further into what might be described as algorithmically mediated governance. In this setting, AI ceases to function merely as an auxiliary analytical instrument. It becomes embedded—structurally—in urban management architectures, influencing both operational routines and higher-order strategic choices. The range of applications is extensive, but unevenly distributed; some domains display relatively high levels of maturity, others remain fragmented, exploratory, not fully stabilized.

Urban mobility constitutes one of the most developed application areas, although even here coherence is not guaranteed. AI-based traffic management systems draw on real-time inputs from heterogeneous sources—sensor networks, video feeds, GPS traces, mobile applications—

to regulate flows and mitigate congestion. Machine learning models extrapolate from historical and current datasets, generating short-term forecasts that allow for dynamic signal control or route optimization. In more advanced configurations, reinforcement learning introduces adaptive control mechanisms, where traffic systems effectively "learn" from ongoing conditions. Yet the effectiveness of these solutions is highly contingent. Data completeness is rarely achieved. Integration across administrative boundaries—particularly in metropolitan regions composed of multiple jurisdictions—often proves difficult. The system works, but only within certain limits (Koshy et al., 2026; Garai et al., 2026; Li et al., 2026; Sungheetha et al., 2026; Wolniak, Stecuła, 2024; Rosak-Szyrocka, Wolniak, 2025a).

In the energy domain, AI applications are closely entangled with the evolution of smart grids and the growing share of renewable energy sources. Urban energy systems are no longer centralized in the traditional sense; they become distributed, variable, sometimes unstable. This introduces the need for more sophisticated coordination mechanisms. AI models support load forecasting, demand-side management, and distribution optimization, enabling more responsive balancing of supply and demand. Predictive analytics can anticipate peak loads, while anomaly detection tools identify inefficiencies or technical faults within the grid. At the same time, the proliferation of distributed energy resources—rooftop photovoltaics, localized storage units—adds layers of operational complexity. AI facilitates coordination, yes, but it also exposes new vulnerabilities. Questions of resilience, of cybersecurity, do not disappear; they intensify (Shrivastava et al., 2026; Pawar et al., 2026; Skotnicka-Zasadzień, Wolniak, 2026).

Public safety and urban security represent another field of rapid AI deployment, particularly through the use of computer vision and predictive analytics. Automated video analysis allows for object detection, crowd monitoring, behavioral pattern recognition—functions that would otherwise require extensive human oversight. Predictive models attempt to estimate spatial or temporal concentrations of risk, informing allocation of policing resources. But this domain remains deeply contested. Issues of privacy, algorithmic bias, and potential discrimination are not peripheral—they are central. Training data may encode existing inequalities; model outputs may reinforce them. In this sense, public safety applications illustrate a recurring asymmetry: technological capacity advances quickly, while regulatory and ethical frameworks struggle to keep pace. Sometimes significantly.

Environmental monitoring and urban sustainability form another domain in which AI is increasingly embedded. Sensor infrastructures generate continuous streams of environmental data—air quality indices, acoustic levels, thermal variations, pollutant concentrations. Machine learning techniques process these inputs to detect trends, forecast risks, and support policy interventions. For example, models can simulate pollutant dispersion patterns across urban morphologies, enabling more targeted mitigation strategies. In water systems, predictive algorithms assist in leak detection, distribution optimization, stormwater management. These applications gain particular relevance under conditions of climate instability, where adaptability becomes a functional requirement rather than a policy preference. Yet, again, a gap appears. Analytical insight does not automatically translate into effective intervention. Institutional fragmentation, limited administrative capacity—these factors intervene.

Beyond sector-specific implementations, a more structural transformation becomes visible through the emergence of integrated, data-driven urban management models. These models attempt to transcend individual domains, linking data flows and decision processes across the urban system as a whole. The notion of the "urban data platform" captures this idea: a centralized or federated environment where heterogeneous datasets are aggregated, standardized, and made interoperable. In principle. In practice, achieving interoperability remains difficult. Data standards differ, ownership structures are contested, technical architectures are not easily aligned. The platform exists, but often in a partial or segmented form (Alourani et al., 2026; Nagpal et al., 2026; Khan et al., 2026).

A related development—more advanced, but also more demanding—is the concept of the digital twin. Here, the city is represented as a dynamic virtual model, integrating real-time data with simulation capabilities. Digital twins allow planners to test scenarios, evaluate interventions, anticipate system responses before changes are implemented in the physical environment. Traffic systems can be simulated under alternative infrastructure configurations; energy transitions can be modeled under different policy assumptions. The incorporation of AI enhances these models, introducing predictive and adaptive dimensions. Still, the resource requirements are substantial. Not only computational, but organizational. Many cities lack the institutional capacity to sustain such systems over time.

Algorithmic governance represents a further step, where decision-making processes are partially—sometimes extensively—delegated to AI systems. This may involve automated service allocation, dynamic pricing mechanisms, real-time optimization of public resources. The potential gains in efficiency and responsiveness are evident. But so are the risks. Accountability becomes diffuse. Decision pathways are not always transparent. Who, precisely, is responsible for an outcome generated by an algorithmic system? And how can such systems be audited, contested, corrected? These are not abstract concerns. They shape the legitimacy of governance arrangements (Archana Reddy et al., 2026; Bodade et al., 2026; Gkikas, Gkikas, 2026).

The transition toward data-driven urban management does not follow a uniform trajectory. Cities differ—economically, institutionally, technologically—and these differences produce distinct implementation pathways. Some adopt comprehensive, top-down strategies, investing in integrated infrastructures and large-scale AI deployments. Others proceed incrementally, focusing on pilot projects or specific functional domains. Hybrid configurations also emerge, often involving public–private partnerships that redistribute both capability and control. Each pathway entails trade-offs. Flexibility versus coordination, scalability versus governance complexity. There is no optimal model, only context-dependent configurations.

The table 2 synthesizes the principal domains of AI application in urban systems by linking them with corresponding data-driven management models and their functional implications. It illustrates a transition from sector-specific implementations toward more integrated, platform-based and algorithmically coordinated forms of urban governance, where data interoperability and real-time analytics play a central role. At the same time, the table highlights that technological capabilities are accompanied by systemic constraints, including data quality dependencies, institutional fragmentation, and emerging ethical and accountability challenges.

Table 2.
AI Applications and Data-Driven Urban Management Models: Domains, Architectures, and System Implications

AI Application Domain	Data-Driven Urban Management Model	Key Functions and Implications
Urban Mobility (traffic, transport systems)	Real-time adaptive traffic management systems	Dynamic signal control, congestion prediction, route optimization; dependence on high-frequency data streams; sensitivity to data gaps
Energy Systems (smart grids, RES integration)	Predictive energy management platforms	Load forecasting, demand-response optimization, distributed energy coordination; increased system complexity and cybersecurity exposure
Public Safety and Security	Predictive policing and video analytics systems	Pattern recognition, risk mapping, automated surveillance; ethical risks (bias, privacy), governance challenges
Environmental Monitoring	AI-supported urban sustainability platforms	Air quality prediction, climate risk modeling, resource optimization; supports evidence-based policy, but requires institutional integration
Water and Waste Management	Smart resource management systems	Leak detection, consumption optimization, waste flow prediction; efficiency gains with relatively low visibility to citizens
Healthcare and Social Services	Predictive service allocation models	Identification of vulnerable populations, demand forecasting; risk of exclusion due to data bias or incomplete records
Urban Planning and Infrastructure	Digital twin-based planning models	Scenario simulation, infrastructure optimization, long-term forecasting; high data and computational requirements
Governance and Administration	Algorithmic decision-support systems	Automation of administrative decisions, resource allocation; issues of transparency, accountability, and legitimacy
Cross-domain Urban Management	Integrated urban data platforms	Interoperability across sectors, centralized or federated data governance; technical and institutional coordination challenges
Citizen Interaction and Participation	AI-enhanced civic engagement platforms	Chatbots, sentiment analysis, participatory data input; potential to increase responsiveness, but uneven adoption across groups

Source: Author’s own work.

4. Conclusion

The integration of artificial intelligence into People Analytics should not be interpreted as a marginal enhancement of existing analytical routines. It is closer to a structural reconfiguration—one that alters how organizational behavior is observed, interpreted, and, eventually, translated into managerial action. The analytical lens shifts. Instead of static, descriptive snapshots of workforce phenomena, AI-driven approaches enable dynamic, multi-level representations in which behavior is understood as an emergent property of interacting elements: individual decisions, relational structures, institutional contexts. Not always neatly separable. Within such a framework, employee behavior appears less as a set of attributes and more as a process—evolving, contingent, sometimes unstable.

This transformation extends both the explanatory and predictive reach of organizational research. AI-based models allow for the identification of complex behavioral configurations associated with engagement, turnover, collaboration patterns, leadership dynamics, or well-being trajectories. These configurations are not isolated variables; they form interdependent structures that unfold over time. The temporal resolution of analysis increases—what was previously observed in aggregated intervals can now be tracked as a sequence of micro-adjustments. Subtle shifts, small deviations. At the same time, analytical granularity deepens, enabling the detection of patterns that remain obscured under conventional statistical approaches. Yet, increased precision does not necessarily imply increased understanding. Not automatically.

The findings suggest that the value of AI-driven People Analytics is not intrinsic to the technology itself but depends on its theoretical and epistemological embedding. Artificial intelligence does not displace established frameworks of organizational behavior. Rather, it repositions them. Theory moves away from a strictly model-specifying role toward a more interpretative function—one that situates algorithmically identified patterns within broader explanatory narratives. This creates a hybrid analytical logic, combining inductive pattern discovery with deductive reasoning. Productive, but also tension-laden. Questions of causality become less straightforward; interpretability varies across models; generalizability remains uncertain, especially when context-specific data dominate the analysis. Without a sufficiently robust conceptual grounding, there is a risk of reducing complex human phenomena to abstract data regularities—precise in form, limited in meaning.

Also the expansion of AI within People Analytics introduces a set of ethical and normative dimensions that cannot be treated as secondary considerations. They are constitutive of the analytical process itself. Issues of privacy, transparency, fairness, and employee autonomy shape not only the acceptability of AI applications but also their operational viability over time. Systems perceived as opaque or intrusive tend to generate resistance, which in turn affects data quality and model performance. A feedback loop emerges—technical and social factors intertwine. Not always predictably.

The further development of People Analytics depends on the capacity to align computational sophistication with forms of ethical governance and contextual awareness. It is not enough to build more accurate models. The challenge lies in embedding these models within organizational settings in ways that preserve trust, maintain interpretability, and respect the complexity of human behavior. A theoretically informed, ethically grounded approach does not resolve all tensions, but it allows organizational research to retain explanatory depth while adapting—sometimes unevenly—to the increasing data intensity and structural complexity of contemporary work environments.

From the findings of this analysis, it is evident that it would be useful for organizations to implement AI-powered People Analytics in a strategic and theoretically informed way, thus making sure that technology is implemented based on organizational behavior theories rather than the availability of data alone or novel ways of using analytics. This suggests the necessity for organizations to implement integrated analytical architectures through which behavioral data from various sources could be analyzed based on theoretical constructs, which would make it possible not only to predict certain outcomes but to interpret employee-related phenomena as well. On the other hand, the use of People Analytics should go hand in hand with investments in analytical capabilities and governance to enable responsible applications of technology. Specifically, special emphasis should be placed on embedding certain ethical considerations, such as the protection of personal privacy, into People Analytics solutions. Otherwise, the analytical benefits provided by AI could be overshadowed by lack of trust and limited applicability of insights gained through analytics.

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