The impact assessment of AI smart city services leveraging High Value Datasets

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Abstract
This paper presents an evaluation framework developed within the BeOpen project to measure the impact of data-driven digital services leveraging High-Value Datasets (HVDs) across multiple smart city pilots in Europe. By integrating artificial intelligence (AI), machine learning (ML), and edge computing, the project targets critical urban challenges, including natural disaster management, sustainable mobility, infrastructure maintenance, and urban resilience. The methodological approach combines quantitative key performance indicators (KPIs) with qualitative insights gathered through stakeholder surveys, interviews, and focus groups. The assessment addresses technical and organizational aspects as well as acceptability and adoption of such AI based services enabled by HVDs, highlighting both achievements and areas for improvement in data interoperability, quality, accessibility, and stakeholder collaboration. Findings demonstrate substantial benefits of using structured and standardized datasets for enhanced decision-making and underline the need for further advancements in dataset interoperability, real-time analytics, and stakeholder engagement.

Keywords
Smart Cities, High-Value Datasets, Artificial Intelligence, Interoperability, Impact Assessment [1]

1. Introduction

The integration of Artificial Intelligence (AI) into public services has advanced rapidly, especially in smart cities, where AI supports urban safety, mobility, environmental monitoring, and emergency response. These trends align with EU strategies such as the [1], [2], and [3]. These developments also align with debates on the role of smart cities in public governance, which some authors argue may reflect competing interests between technological empowerment and political-economic agendas. However, implementing AI in public service delivery raises critical questions about societal impact, trust, accountability, and data governance. While AI's potential is widely recognized, assessing its real-world effects remains complex [4], [5]. Research on open data and algorithmic governance has highlighted both the benefits and limitations of AI in the public sector, with factors like adoption barriers, data quality [6], [7], institutional readiness, and local context playing a central role in shaping outcomes. Public sector capacity and stakeholder engagement are equally vital for generating public value. As a result, robust evaluation frameworks are needed to assess not just technical performance [8], [9], but also societal acceptance and impact. This paper addresses this need by presenting an impact assessment framework developed in this [10] EU-funded initiative aimed at co-designing and deploying AI-powered digital services using High-Value Datasets (HVDs), bringing together European universities, research centres, municipalities, and digital providers to support evidence-based policymaking and promote trust in AI through user-centric, interoperable solutions [11], [12]. The framework was applied in ten pilot use cases in eight cities, in domains such as safety, emergency response, and mobility. These pilots integrate open and proprietary datasets and test the operational, economic, and societal impact of AI-based services. While the broader framework includes long-term impact analysis [13], this paper focuses on the early stages, evaluating their acceptance and adoption in urban safety contexts. Content: Section 2 - the methodology and the ten use cases in eight Pilot

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Cities. Section 3 - the context on smart city challenges. Section 4 - the baseline findings across the pilots. Section 5 - the policy implications and recommendations for scaling AI-based public services.

2. The impact framework, the approach to data collection and the use-cases

The BeOpen project adopts a mixed-method evaluation framework to assess the impacts of AI-based digital services leveraging HVDs. This framework combines quantitative analysis through predefined Key Performance Indicators (KPIs) with qualitative insights gathered from multiple stakeholder groups. The aim is to capture the multifaceted effects—economic, social acceptance, organisational, and technological—of BeOpen interventions across ten smart city pilots. By integrating KPI tracking with stakeholder perceptions and contextual observations, the methodology enables both comparative assessment across use-cases and in-depth understanding of local dynamics. This section outlines the approach to data collection and analysis used to operationalise this evaluation framework. The section presents the evaluation framework and data collection approach adopted by BeOpen to assess the impacts of AI-enabled digital services powered by High-Value Datasets (HVDs). Combining quantitative KPIs with qualitative stakeholder input, the framework captures the multifaceted effects—economic, social, organisational, and technological—across ten smart city pilots. Sub-sections 2.1 and 2.2 outline the methodological foundation and data collection strategy, while 2.3 introduces the scope of each pilot and its specific use of AI and HVDs.

2.1. The BeOpen Impact Framework

The evaluation framework presented and tested in this paper originates from the BeOpen project and is designed to assess the adoption and effectiveness of AI-based digital services built upon High-Value Datasets (HVDs) in urban safety and mobility contexts. The framework follows a structured intervention logic, aligning project objectives with measurable outcomes. Specifically, it derives Key Performance Indicators (KPIs) from overarching objectives, which are translated into specific, operational indicators to monitor both project-wide and use-case-specific progress. These indicators are organized around canonical evaluation criteria recommended by the OECD and adapted for digital government and AI maturity contexts [13], [5]. The criteria include: effectiveness, efficiency, relevance, replicability, and scalability, alongside an AI-specific maturity dimension. The AI maturity model applied here captures the readiness and adoption of AI tools within the urban environment. Indicators were developed through a combination of literature review (e.g., [6]; [9]), existing evaluation models for AI deployment [4]; [5], and the internal methodology outlined in [14] The table below presents the Impact Assessment Framework (IAF), mapping each criterion to its corresponding indicators, evaluation objective, and source.

Table. 1. *Proposed IAF developed to map AI based services in smart cities enabled by HVDs*

Criterion	Indicators	Objective	Source
Data Availability and Quality	Completeness, accuracy, update frequency, metadata availability	Ensure high-quality, timely, and relevant data for AI applications	[14]; [9]
AI Strategy and Governance	AI roadmap, policy alignment, leadership structure	Evaluate strategic alignment and institutional readiness for AI	[14]; [2]
Technological Infrastructure	IoT compatibility, interoperability, platform readiness	Assess ability to support advanced AI and data infrastructure	[14]

Criterion	Indicators	Objective	Source
AI Expertise and Talent	Internal skills, partnerships, training plans	Identify workforce readiness and support for AI implementation	[14]; [5]
AI Model Development	Robustness, explainability, continuous learning mechanisms	Measure the maturity and adaptability of AI models	[14]; [13]
System Integration	Integration with legacy systems and public services	Ensure embedding of AI into existing systems	[14]
Scalability and Flexibility	Multi-domain applicability, modularity	Enable replication and adaptation of solutions	[14]
Performance Monitoring	Use of KPIs, dashboards, feedback loops	Track effectiveness and promote continuous improvement	[14]; [13]
Community Engagement	Citizen co-design, pilot participation, communication mechanisms	Enhance legitimacy and social sustainability	[14]; [4]
Regulatory Compliance	GDPR, AI Act, mobility regulation alignment	Ensure ethical and lawful AI usage	[14]; [3]
User Experience & Accessibility	Interface simplicity, multilingual support, inclusiveness	Promote usability and accessibility for diverse users	[14]
Cost Efficiency	ROI, cost per user, operational savings	Evaluate economic viability of AI deployments	[14]
User Acceptance & Satisfaction	Survey feedback, adoption rates, usage statistics	Assess end-user engagement and satisfaction	[14]

Particular attention is also given to data quality, which is essential for trustworthy and effective AI systems. Poor-quality datasets—characterized by missing values, inconsistencies, or outdated information—can compromise model accuracy and lead to poor decision-making. As such, data validation and cleansing processes are included in the framework, aligned with best practices for ensuring AI readiness [9]. The IAF incorporates capabilities for data enrichment, monitoring, and alerting, ensuring that data used for AI applications is complete, consistent, and contextually appropriate.

2.2. Approach to data collection

The BeOpen project adopts a structured mixed-methods approach to data collection to ensure a comprehensive evaluation of AI-based digital services that leverage HVDs. This methodology is designed to capture the economic, social, organisational, and technological impacts of digital transformation across ten smart city pilots (section 4). Informed by established frameworks described in this section , the approach integrates both quantitative and qualitative methods to support data triangulation and robust assessment [15], [16], [17]. Data are collected through a stakeholder survey, semi-structured interviews, project implementation logs, usage metrics from the digital portals, and participatory focus groups. The stakeholder survey, initially designed in English and translated into the local languages of the pilots, includes both general cross-use-case questions and specific modules tailored to different stakeholder categories, including public authorities, SMEs, researchers, and citizens. Descriptive statistics are used for initial analysis, with inferential statistics applied where scale permits, to extract patterns and measure the perceived effectiveness and usability of the AI-enabled services. The survey is complemented by semi-structured interviews, designed around a flexible yet structured guide. These interviews aim to collect deeper insights into the social, institutional, and economic effects of the BeOpen interventions. The qualitative findings help interpret the survey data, revealing motivations, perceived risks, barriers to adoption, and contextual factors influencing impact. The use of interviews as a complementary method aligns with established practices in digital government evaluation [18]. In addition to stakeholder perceptions, project implementation logs maintained by pilot leaders document procedural milestones, decision-making processes, and operational challenges. These logs contribute to understanding how services evolve over time and provide internal evidence of implementation progress. Metrics from the digital portals—such as user interactions and service uptake—offer real-time, quantitative data to support evaluation of the usability and scalability of services. Participatory focus groups are convened to validate the interim results of surveys and interviews and to refine policy-relevant conclusions. These sessions are conducted in each pilot site and involve a range of stakeholders, enabling bottom-up feedback. The participatory element reflects contemporary citizen engagement strategies in smart city governance and supports co-creation of AI services [19]. This integrated data collection strategy is operationalised through a shared toolbox developed by the BeOpen consortium [14], which facilitates a comparative analysis of pilot results, supports longitudinal monitoring of long-term outcomes, and provides structured mechanisms for continuous feedback. The toolbox also informs local and EU-level policy decision-making by linking insights from field data to broader digital governance objectives. In this way, the approach builds on existing impact evaluation frameworks while tailoring them to the specifics of HVD-based AI services, ensuring both analytical rigour and practical relevance. This integrated data collection strategy lays the groundwork for the subsequent section, which outlines the scope of the ten BeOpen pilots in applying AI-based solutions enabled by HVDs

2.3. BeOpen Pilots and Use Cases

All BeOpen pilot cases make use of HVDs that adhere to the principles of openness, interoperability, and societal impact as defined under the EU Open Data Directive. Whenever legally and ethically permissible, datasets are open, publicly accessible, or designed for reuse across cities and sectors. In cases involving sensitive information (e.g., mobility or video data), strict data governance frameworks ensure compliance with GDPR and national privacy regulations, while enabling secure, pseudonymised, or aggregated data sharing where relevant. Shared datasets are prioritised when they enhance cross-city learning and model transferability. This approach strengthens both local and EU-wide scalability of digital solutions and aligns with the FAIR data principles. References to existing open datasets (e.g., Copernicus, EFFIS, Eurostat) are included where applicable, and all pilots contribute to a federated data ecosystem fostering transparent and responsible data reuse.

Pilot 1: Attica – Natural Disaster Shield. Problem: Rising wildfire risks to urban and natural areas. Datasets: Fire records, social media reports, EFFIS indices, satellite data. Digital Services: AI-based early warning system using social and satellite signals. Results: Faster detection, improved emergency response, stronger resilience.

Pilot 2: Cartagena – Urban Safety & Sustainability Dashboard. Problem: Balancing public safety and energy efficiency under climate pressure. Datasets: Traffic, lighting, air quality, satellite data. Digital Services: Real-time urban safety and environment dashboard. Results: Safer streets, better climate policy, efficient lighting.

Pilot 3: Torre Pacheco – Environmental Livability Monitoring. Problem: Pollution impacting public health. Datasets: IoT sensors for air, noise, weather. Digital Services: AI-based pollution prediction with user dashboard. Results: Data-driven mitigation and improved planning.

Pilot 4: Molina de Segura – Transparent Air Quality System. Problem: Disconnected data limits environmental response. Datasets: Air quality, weather, long-term pollution indices. Digital Services: Public dashboard for real-time air monitoring. Results: Greater trust, better policies, increased accountability.

Pilot 5: Herne – Smart Road Maintenance. Problem: Reactive, costly road repairs. Datasets: Degradation data, traffic, maintenance logs. Digital Services: AI for defect detection and planning. Results: Safer roads, cost savings, better investments.

Pilot 6: Herne – Large-Scale Event Management. Problem: Emergency risks during crowded events. Datasets: Mobility, emergency logs, video feeds. Digital Services: Real-time AI alerts and monitoring. Results: Faster responses and safer gatherings.

Pilot 7: Porto – Urban Flood Forecasting Problem: Climate-driven flood threats. Datasets: Rainfall, river flow, terrain, past floods. Digital Services: AI flood prediction and alerts. Results: Better preparedness, reduced risk, resilient infrastructure.

Pilot 8: Porto – Emergency Response Dashboard. Problem: Disjointed incident management. Datasets: Dispatch logs, geolocation, team data. Digital Services: Dashboard for real-time coordination. Results: Quicker, more efficient emergency responses.

Pilot 9: Naples – Sustainable Mobility Planning Problem: Inefficient transport contributing to pollution. Datasets: Transit data, air quality, emissions metrics. Digital Services: AI for transport-environment integration. Results: Lower emissions, improved mobility, better planning.

Pilot 10: Vilnius – Biodiversity Protection with AI Problem: Invasive species harming ecosystems. Datasets: Satellite images, species tracking, climate models. Digital Services: AI mapping and detection tools. Results: Early action and smarter biodiversity management

3. Context and challenges in the BeOpen smart cities

In flood prediction and groundwater management, AI-driven models enhance both forecasting and monitoring capabilities. In flood control, machine learning integrates diverse data sources (e.g., radar feeds, social media, IoT sensors) to enable real-time predictions, often outperforming slower physics-based models. These data-driven approaches improve the timeliness and accuracy of flood warnings, supporting earlier and more targeted responses [20], [21]. Evaluation of AI in this domain focuses on predictive performance, measured against observed hydrological events. For groundwater, hybrid models combining satellite imagery, climate data, and extraction records improve the completeness and granularity of datasets and offer early detection of contamination or depletion. Despite progress, challenges remain due to fragmented data and complex subsurface dynamics [22]. The MAR2PROTECT project exemplifies an AI-based decision support tool that models scenarios of contamination and over-extraction [23]. In traffic optimization, AI applications process live GPS, road sensors, and CCTV data to regulate traffic signals and optimize routes in real time. The real-time nature of data enhances system responsiveness, while accuracy and availability are critical for reducing congestion. Pilots like the Barcelona smart traffic control system report up to 30% fewer stop-and-go patterns, with evaluation metrics including reduction in travel time and CO_2 emissions [24], [25]. Scalability, transparency, and fairness remain key concerns when integrating such systems city-wide [26]. For Urban Heat Island (UHI) mitigation, AI models use high-resolution thermal imaging and environmental data to detect heat stress patterns at the neighborhood level. These systems require spatial granularity and temporal resolution to assess heat vulnerability accurately. Interventions (e.g., green roofs, reflective surfaces) are prioritized based on AI simulation outputs, which are evaluated through scenario comparisons and stakeholder feedback loops [27], [28]. AI in smart lighting helps cities transition to energy-efficient LED systems. While LED adoption reduces energy costs, health implications due to spectral composition (blue light exposure) are being monitored. AI systems analyze ambient conditions and pedestrian presence to implement adaptive lighting schemes. Performance evaluation considers energy savings, safety outcomes, and citizen feedback on light intensity and glare [29], [30], [31]. For invasive species monitoring, AI models leverage computer vision and citizen science inputs to automate identification and geotagging. High classification accuracy and report validation are key for timely interventions. Initiatives like Mosquito Alert integrate deep learning with participatory data, evaluated based on detection rates and false positives [32], [33], [34]. Crowd management systems now integrate AI with IoT sensors and wearable devices to monitor density and detect anomalies during events. Evaluation metrics include response time, detection accuracy, and stakeholder satisfaction. The MONICA project exemplified this by successfully identifying and managing congestion in real-time using smart CCTV and sensor arrays [35], [36]. In infrastructure monitoring, AI-based predictive maintenance tools process vibration data, drone imagery, and traffic loads to forecast degradation. Data completeness, accuracy, and continuity are critical. Projects like CROWD4ROADS illustrate how mobile sensor data can map surface roughness, with AI-driven insights guiding proactive maintenance [37], [38]. AI also contributes to urban energy management by optimizing consumption patterns and facilitating the integration of renewables. Smart grids adjust electricity flow based on real-time data, improving availability and reliability of supply. AI-based building management systems reduce energy use by adapting HVAC and lighting to occupancy and external conditions. Impact is assessed through energy savings, user satisfaction, and carbon footprint reduction [39], [26].

4. Preliminary results: the Baseline analysis and Impact Assessment of the Use Cases in Pilot Cities

This section presents the baseline assessments for the 10 pilot use cases, highlighting key quantitative and qualitative findings before the full rollout of AI-powered services. Guided by the mixed-method evaluation framework from Section 2, the assessments combined KPIs with stakeholder engagement and contextual analysis. Tools included the Metadata Quality Validator (to assess compliance with DCAT-AP), stakeholder mapping and engagement logs, and a KPI tracking dashboard covering economic, social, organizational, and technological aspects. Full tool documentation is provided in project deliverables [10] [14].

4.1. Use Cases in City Pilots Outlook

The BeOpen pilot cities tackle varied urban and environmental challenges using HVDs and AI-driven tools. Attica focuses on wildfire detection; Cartagena, Torre Pacheco, and Molina de Segura use data platforms to enhance safety, lighting, and climate resilience. Herne applies AI to road maintenance and event management, while Porto improves flood forecasting and emergency response. Naples integrates mobility and environmental data, and Vilnius monitors invasive species. These cases show how AI-based solutions enhance decision-making, sustainability, and public services across Europe. Table 2 summarises the problems, cities, and key baseline findings.

__Table. 2.__ Pilot cities and use cases in brief

Use Case #	City – Use Case	Problem	Quantitative Findings and Baseline Results
1	Attica (GR) – Natural Disaster Shield	Increasing frequency/severity of wildfires threatening urban areas and ecosystems	3.5x faster detection using AI; 95% event match with Copernicus/EFFIS data
2	Cartagena (SP) – Data Visualization Platform	Urban safety, LED lighting, and climate change mitigation	Air quality data matched 87% with official sources; safety perception up by 40%
3	Torre Pacheco (SP) – Data Visualization Platform	Noise and air pollution affecting urban health	>100 sensor installations; 25% improvement in data resolution and coverage
4	Molina de Segura (SP) – Data Visualization Platform	Need for environmental monitoring and air quality assessment	Real-time platform used by 200+ users; 30% increase in citizen engagement
5	Herne (DE) – AI for Street Management Investments	Inefficient infrastructure maintenance planning	Road condition index improved by 15%; 20% cost savings projected
6	Herne (DE) – Large-Scale Events and Civil Protection	Managing crowd safety and emergency response during major events	Event simulations showed 30% faster response times; optimized deployment of emergency units
7	Porto (PT) – Urban Flood Forecast	Urban flooding risks due to climate change	Flood prediction accuracy improved by 25%; alert system reduced response time by 40%
8	Porto (PT) – Emergency Teams Visualization Dashboard	Fragmented emergency response coordination	Dashboard cut incident reporting lag by 50%; live tracking used in 80% of events
9	Naples (IT) – Mobility & Environment Data Integration	Fragmented data for transportation and environmental planning	Emission estimates reduced by 12%; better public transport planning validated in 3 scenarios
10	Vilnius (LT) – Invasive Species Spread Forecast	Threats to biodiversity from invasive species	Detection precision reached 85%; species mapping accuracy improved by 20%

4.2. Preliminary results of the technical feasibility and adoption of AI solution and HVDs in Pilot Cities

To complement the framework in Section 2 and the evaluation criteria in Table 1, the following table summarizes the AI-readiness and maturity levels across the ten BeOpen pilots. Each criterion is assessed along three dimensions: (i) technical applicability, (ii) organizational readiness, and (iii) level of adoption. Ratings—High (H), Medium (M), or Low (L)—are based on evidence from baseline assessments, stakeholder input, and KPI tracking. Some criteria are not applicable to all dimensions.

For example, AI Expertise and Talent is relevant only to organizational readiness, while System Integration and Cost Efficiency are mainly technical or organizational, with limited relevance to adoption. These cases are marked as “n.a.” in the table.

Table. 3. *Preliminary results of the application of the BeOpen IAF across all Pilots*

Criterion	Indicators	Technical Applicability	Organizational Readiness	Level of Adoption
Data Availability and Quality	Completeness, accuracy, update frequency, metadata availability	H	M (Herne (H), Athens (L))	M (Lisbon (H), Athens (L))
AI Strategy and Governance	AI roadmap, policy alignment, leadership structure	M (Naples (L))	M (Vilnius (H), Naples (L))	M (Athens (H), Naples (L))
Technological Infrastructure	IoT compatibility, interoperability, platform readiness	H (Naples (M))	M (Athens (H), Naples (L))	– (Not applicable)
AI Expertise and Talent	Internal skills, partnerships, training plans	– (Not applicable)	M (Naples (L), Herne (H))	H (Vilnius (M), Naples (L))
AI Model Development	Robustness, explainability, continuous learning mechanisms	M	M	M (Athens (H), Naples (L))
System Integration	Integration with legacy systems and public services	H (Lisbon (L))	H (Athens (M), Naples (L))	– (Not applicable)
Scalability and Flexibility	Multi-domain applicability, modularity	M	M (Lisbon (H), Athens (L))	M (Herne (H), Naples (L))
Performance Monitoring	Use of KPIs, dashboards, feedback loops	M (Athens (L), Naples (H))	M (Naples (L), Herne (H))	M (Lisbon (H), Naples (L))
Community Engagement	Citizen co-design, pilot participation, communication mechanisms	L (Naples (M))	M (Athens (H), Naples (L))	M (Herne (H), Naples (L))
Regulatory Compliance	GDPR, AI Act, mobility regulation alignment	H	M (Lisbon (H), Athens (L))	– (Not applicable)
User Experience & Accessibility	Interface simplicity, multilingual support, inclusiveness	M	M (Athens (L), Naples (H))	H (Herne (M), Naples (H))
Cost Efficiency	ROI, cost per user, operational savings	H	H (Athens (M), Naples (L))	– (Not applicable)
User Acceptance & Satisfaction	Survey feedback, adoption rates, usage statistics	M (Herne (H), Naples (L))	M (Athens (L), Lisbon (H))	M (Naples (L), Vilnius (H))

The assessment reveals a generally positive level of technical applicability across the BeOpen pilot cities, especially regarding data and infrastructure. Data Availability and Quality scored high in all pilots, showing strong dataset completeness, metadata structure, and update frequency—suitable for AI-based services. AI Strategy and Governance scored moderate in Technical Applicability, being more reliant on institutional conditions. It rated high in Organizational Readiness in cities like Herne, where AI roadmaps exist, and low in others like Naples, which lack formal strategies. Technological Infrastructure was rated high in Technical Applicability, supported by existing IoT systems and platform readiness, though not assessed under Level of Adoption, as deployment was not always part of the pilot scope. AI Expertise and Talent was not assessed technically but showed organizational variation: Herne and Porto had strong training or partnerships, while Naples lacked internal capacity. AI Model Development scored medium across the board, as most cities experimented with explainable models, but robustness and adaptability remained limited. System Integration scored high technically due to successful interfacing with legacy systems, though full integration was often beyond the pilot's scope. Scalability and Flexibility scored medium, reflecting proposed modular designs with limited cross-domain reuse during the pilot. Performance Monitoring was also rated medium, with KPI dashboards and feedback loops introduced but not systematically used in decision-making. Community Engagement varied: Herne and Porto scored high due to early co-design efforts, while Naples showed low engagement, involving stakeholders mostly at later stages. Regulatory Compliance achieved high Organizational Readiness in all cities, especially regarding GDPR, but was not assessed in Adoption, as compliance is a prerequisite. User Experience & Accessibility scored medium, with cities like Herne slightly ahead due to more refined interface design. Cost Efficiency was rated medium for Technical Applicability and Organizational Readiness, reflecting initial ROI monitoring, though not assessed in Adoption due to pilot timeframes. User Acceptance & Satisfaction also varied: Herne and Porto reported high engagement and positive user feedback, while Naples had limited interaction and satisfaction data. Overall, cities with strong digital infrastructure, stakeholder engagement, and governance (e.g., Herne, Porto) showed higher readiness and adoption, while cities facing institutional or technical gaps (e.g., Naples) scored lower. These insights support targeted investment in skills, governance, and infrastructure to strengthen weak points and foster cross-city learning.

5. Conclusions and Policy implications

This paper has summarized the outcomes of a baseline assessment conducted across eight pilot cities within the BeOpen project, examining the availability and use of HVDs, as well as the technological and organizational readiness for adopting AI-driven digital services. Using the evaluation criteria outlined in Table 1 (Section 2), the analysis reveals significant variation in data integration, quality, and system maturity across cities. Geospatial data has been relatively well integrated, confirming its foundational role in mobility and environmental planning. However, other categories of HVDs—such as those related to company ownership and mobility—remain underused despite their potential value. This highlights the need for further investment in infrastructure, data standardization, and mechanisms to engage stakeholders effectively. From a technical standpoint, the cities show moderate levels of interoperability and integration, but most still lack advanced analytics capabilities, real-time data use, and strong AI governance frameworks. Organizational challenges persist in terms of internal capacity, leadership, and coordination, and most cities report only moderate effectiveness of their existing data management systems. This underlines the importance of aligning future digital services with actual capacity and user needs. The analysis also points to a broader issue: HVDs are not yet embedded in daily decision-making or public engagement processes. Their transformative potential remains limited by fragmented access, a lack of digital skills, and inconsistent governance. Addressing these challenges requires a comprehensive policy approach that connects technological advancements with social innovation and institutional reform. Further research should aim to test the BeOpen framework in other European and global cities to assess its scalability and adaptability. Longitudinal studies comparing baseline and post-implementation data will be needed to measure impact, while refining indicators related to stakeholder engagement and service effectiveness will support more user-centred policy design. Greater integration of AI-readiness metrics into smart city strategies is also needed, in line with evolving EU regulations such as the [3] and the Data Governance Act. At the EU level, the findings reinforce the need to promote harmonization and standardization across Member States, particularly regarding metadata, dataset quality, and interoperability. Frameworks like DCAT-AP should be further supported. At national and local levels, investments should prioritize digital infrastructure, capacity-building, and ethical AI governance. Smart city design should focus on modular, scalable solutions with embedded monitoring and feedback systems. Ultimately, this research confirms that the value of HVDs can only be fully realized when technical innovation is coupled with social, organizational, and regulatory progress. The BeOpen framework provides a structured foundation for guiding cities toward more data-informed, resilient, and citizen-focused digital transformation.

Declaration on Generative AI

AI Large Language Models were used for academic literature review and to revise the English language.

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