CityMindX:AI-Based Mobility and Infrastructure Optimisation in Smart Cities

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Abstract— Nowadays, artificial intelligence (AI) plays an increasingly important role in addressing sustainability challenges. There is a lack of comprehensive smart city solutions that integrate both technological and social dimensions. To fill this gap, this research focuses on developing the CityMindX framework: an integrated, three-layer AI architecture aimed at the holistic optimisation of urban mobility and infrastructure systems by combining social science and data science methodologies. The research encompasses the theoretical framework of the CityMindX concept, the analysis of the functioning of the architecture by processing four case studies, and the empirical validity of the concept is tested by statistical analysis of a quantitative survey (mixed methodological). The novelty of the proposed approach lies in the fact that it is the first to integrate technological (edge–fog–cloud layering, federated learning) and social elements (e.g., public trust, inclusive governance) within a triple AI framework, complemented by the application of explainable and trustworthy AI principles in a smart city model. The findings indicate that the application of CityMindX can bring systematic improvements to the coordination of urban subsystems (e.g., transportation, energy), reducing parallel burdens (e.g., environmental impacts from simultaneous peak traffic) and making city operations more adaptive. The research confirmed that technological advancement directly and indirectly enhances urban well-being, while public trust and social inclusion play a key mediating role in achieving these positive effects. The results highlight that CityMindX can facilitate sustainable and inclusive smart city development, offering policymakers a practical tool to improve urban services and residents' quality of life.

Keywords: AI architecture, digital inclusion, smart cities, urban resilience, XAI

JEL- Code: O33, O18, Q01, R58, O38

I. INTRODUCTION

The problem's nature, prior research, the paper's objective, and its contribution should all be explained in the introduction. For ease of comprehension, the co The mobility and infrastructure systems of modern cities are becoming increasingly complex, while challenges such as urban population growth, traffic congestion, and the climate crisis demand rapid, innovative solutions. Although the concept of the ”smart city” holds great promise, in reality, urban IT and transportation systems often operate in isolated, parallel structures, with limited communication between themselves and with citizens. This hinders data-driven decision-making, broad public engagement, and the effective management of sustainable urban development (Albino et al., 2015; van Winden & van den Buuse, 2017).

One of the aims of the CityMindX project is to develop an integrated, AI-based triple-layer (“triple AI”) urban architecture that simultaneously employs edge and cloud computing, incorporates federated learning and explainable (XAI) models, and integrates early warning systems (AI-EWS) into the urban environment. This comprehensive approach enables the optimisation of traffic congestion, air pollution, and energy consumption, thereby improving quality of life and supporting the achievement of the United Nations Sustainable Development Goals – especially SDG 11: Sustainable Cities and Communities.

Another goal of the CityMindX project is to explore the attitudes of urban professionals and stakeholders toward the triple AI architecture, decentralised (Edge–Fog–Cloud) computing models, federated learning, explainable AI (XAI), and digital inclusion and social participation.

The survey research investigates the following in relation to the eight elements of the CityMindX framework perceptions of urban AI infrastructure and architecture; transparency, trust, and fairness of AI systems; digital inclusion, acceptance of AI-based services, and perceived urban quality of life.

The study analyses the cities of Miskolc and Zalaegerszeg in Hungary, as well as Barcelona and Amsterdam, to derive broader conclusions for Hungarian and European-level smart city developments.

As part of the research, a pilot project is also planned to test the identified gaps practically. The pilot will implement and evaluate the CityMindX "triple AI" system and its predictive models in a real Hungarian urban environment. A significant portion of smart city initiatives never progress beyond the pilot phase and fail to scale to the city or regional level. Van Winden & van den Buuse (2017) point out that smart city pilots often remain "low-budget demonstrations" with limited impact on urban development. Similarly, Bundgaard & Borrás (2021) highlight a recurring "scaling gap" between project-level innovation and city-scale implementation, often hindered by institutional, regulatory, and collaboration-related factors.

The CityMindX framework aims to bridge this scaling gap by prioritising sustainable implementation, replicability across multiple cities, and cost–benefit analysis in the design of the pilot. According to international literature, successful urban innovation scaling requires that pilot results are robustly supported from economic, social, and institutional perspectives. In addition, the long-term viability of pilots also depends on integrated urban governance and data management frameworks. The cost–benefit analysis conducted as part of the project supports the evaluation of the technology's economic and societal utility, aligning with the goals of the UN Sustainable Development Agenda (United Nations, 2015).

Thus, the pilot will not remain an isolated experiment but will serve as the cornerstone of the long-term, multi-city, sustainable, and scalable CityMindX model.

II. THE CITYMINDX FRAMEWORK IN LIGHT OF THE LITERATURE

A smart city is an urban concept that uses information and communication technologies (ICT) to improve the quality of urban life, increase service efficiency, and ensure sustainability. While there is no single unified definition of the term "smart city", it is generally understood as the effective integration of physical, digital, and human systems within a city to provide a sustainable, prosperous, and inclusive future for its citizens. According to Gracia et al. (2023), the definition of a smart city spans multiple domains (transportation, energy, healthcare, education, governance, etc.). It refers to a networked urban environment designed to improve the quality of life and promote sustainability.

A truly "smart" approach can only be realised if technological innovations are implemented not in isolation but within the framework of community participation, human factors, and socio-environmental sustainability. The technology-centric model of the smart city has been criticised in numerous studies, which advocate for a more citizen-focused, participatory, and human-experience-driven "human-centric" smart city paradigm (Alverti et al., 2018; Becker et al., 2023; Han & Kim, 2021; Oh & Seo, 2021). These studies emphasise that smart city developments can only be considered legitimate if public involvement, social justice, and "smart social sustainability" – that is, the improvement of human context and quality of life – are treated with the same importance as the technological infrastructure (Alverti et al., 2018; Becker et al., 2023).

Over the past decade, increasing attention has been paid to how AI can be aligned with the goals of sustainable urban development, particularly those of the United Nations **S**ustainable **D**evelopment **G**oals (SDGs). AI is playing an increasingly prominent role in addressing sustainability challenges – ranging from energy efficiency and urban mobility to environmental monitoring and climate resilience – and is directly linked to achieving SDG 11 and other urban-focused goals (Toderas, 2025; Al-Raeei, 2024). However, AI-based solutions can only credibly support sustainable urban development if they are explicitly linked to the SDG framework, participatory processes, and ethical-governance principles.

Current smart city concepts typically emphasise IoT sensors, data integration, and analytics. Smart city systems often involve the deployment of thousands of sensors – for traffic and environmental monitoring, smart lighting, and data-driven services – which feed into centralised data centres or cloud platforms for analysis.

To date, AI applications have primarily focused on predictive analytics and automation – for example, forecasting traffic congestion or improving the efficiency of energy grids – but they tend to operate in separate, siloed modules. In contrast, the CityMindX concept envisions a more comprehensive, multi-level AI system for the city. Its goal is to integrate previously fragmented solutions and synchronise systems as a "city brain." Whereas traditional platforms emphasise the supervision of specific subsystems (transport, energy, waste, etc.), CityMindX is based on the cooperation of dual- or triple-agent AI systems (a multi-agent architecture). The core issue is that current systems do not manage interactions between subsystems effectively, making holistic optimisation difficult.

CityMindX offers a better alternative: for instance, one AI layer continuously analyses incoming data, another uses generative AI to develop scenarios and plans, and a third adjusts control parameters in real time. Therefore, the advantage of CityMindX lies in its coordinated decision-making enabled by multiple AI agents, which is presumed to respond more effectively to urban challenges and sustain long-term sustainability compared to existing platforms.

Table 1. The CityMindX Framework

1. Smart City (social, environmental, and economic goals)	**2. Decentralised Architecture** (edge-fog-cloud hierarchy)	**3. Data Protection and Accountability** (Trustworthy AI=TAI)	**4. Prediction** (mobility and energy analytics)
5. Explainable AI (transparent decision support)	**6. AI-EWS** (emergency forecasting)	**7. Sustainable Development Goals** (climate adaptation and innovation)	**8. (Dynamic) Cost–Benefit Analysis** (evaluation of urban innovations)

Source: Author's compilation (2025)

The CityMindX framework is based on the coordinated integration of several interrelated scientific domains. Here, we explore how the eight components of the CityMindX framework are reflected in the academic literature (**Table 1.**).

1. Smart City

Albino et al. (2015) and Becker et al. (2023) emphasise that technological innovations can be considered sustainable and inclusive only if they advance alongside social, environmental, and economic goals. CityMindX aligns with all three objectives.

2. Decentralised Computing Architecture

It applies both "dual AI" (edge+cloud) and "triple AI" (edge–fog–cloud) layered approaches. According to Shi et al. (2016) and Mouradian et al. (2018), this layered architecture enables real-time data processing, reduces latency, and improves reliability in urban AI systems. The concepts of dual and triple AI represent a multi-agent approach in which multiple partially independent AI "agents" work together. In such systems, agents operate autonomously, each with its own set of knowledge and objectives, yet solve complex problems cooperatively – tasks that a single AI could not accomplish alone (Truefoundry, 2025). For example, in CityMindX, one AI agent optimises traffic (including signal systems and vehicles), another manages energy distribution (network control), and a third handles supply chains and waste management. Together, they contribute to the city's healthier operation. Dual AI can be imagined as a single layer (e.g., a neural network) that processes and classifies sensor data in real time. In contrast, another layer (another AI module) makes strategic-level decisions based on this analysis. Triple AI goes further – for example, by involving a generative language model in citizen communication and the creation of planning scenarios. Specific application scenarios include traffic management: while one AI adjusts traffic signals, a second AI chain simultaneously proposes and simulates new routes (in cooperation with a digital twin), and a third AI oversees system security and performance. This cooperation among AI agents enables integrated operations that go beyond static automation. The advantages of multi-agent AI could soon be harnessed in smart cities: connecting urban digital twins with generative AI opens the door to large-scale, data-driven scenario and infrastructure planning (Truefoundry, 2025; Xu & Omitaomu, 2024).

Edge AI refers to AI processing that occurs directly at the edge of the network – on sensors, IoT devices, cameras, or local servers – rather than transmitting all data to a central cloud (Shi et al., 2016). Its main benefits include real-time responsiveness, reduced network load, and greater data privacy, as sensitive data remains in the local environment.

Within the CityMindX framework, Edge AI is responsible for real-time assessments of mobility and infrastructure, and for rapidly generating pre-processed decision recommendations.

Fog and Cloud AI refer to a multi-layered computing architecture in which more computation-intensive data processing occurs at the regional "fog layer" (fog computing) or within the infrastructure of global cloud providers (Chiang & Zhang, 2016). The fog layer sits between the edge and the cloud, reducing latency and offloading network traffic. In contrast, the cloud is suitable for large-scale and complex data models, such as deep learning or simulations. In the CityMindX architecture, Fog/Cloud AI is responsible for city-level optimisation, predictive modelling, rule-based and ML-based simulations, and ensuring interoperability between various edge components.

Federated Learning in the CityMindX system refers to a machine learning paradigm that allows models to be trained in a decentralised manner while keeping data local. Instead of sending sensitive data to a central server, local devices share only model updates (parameters, gradients) with a central aggregator (Kairouz et al., 2021; Li et al., 2020). This significantly enhances data security and GDPR compliance, while enabling learning from large, heterogeneous data environments.

In sum, the integration of the edge and cloud hierarchies, the fog layer, and federated learning is essential to CityMindX's decentralised urban AI frameworks, ensuring real-time optimisation and data security.

3. Data Protection, Accountability, and Transparency

Trustworthy AI (TAI) is a central requirement defined by the EU and OECD AI guidelines. According to these, urban AI systems must operate transparently, ensure explainability, provide adequate data protection, and maintain human-centred governance (European Commission, 2019; OECD, 2024). Much of the data generated by urban AI systems is personal or related to public services (e.g., mobility patterns, energy consumption, public safety information), making data protection and ethical usage paramount. In line with GDPR, the CityMindX concept favours local processing of sensitive data using edge devices, minimising centralised data storage.

Overall, the priorities of the CityMindX framework – data security, ethical compliance, and social inclusion – are aligned with international principles for responsible AI development.

4. Predictive Analytics and Machine Learning

These technologies are applicable within the CityMindX smart city and revolutionise urban infrastructure management. Shulajkovska et al. (2024) and Salhi et al. (2025) demonstrate that predictive analytics and machine learning support the optimisation of mobility, energy, and environmental monitoring systems. Intelligent waste management systems, built on real-time IoT data, improve recycling rates and optimise logistics (Alaoui et al., 2025; Maciel et al., 2025). IoT technologies also support predictive maintenance and route-optimisation models, reducing the risk of malfunctions and ensuring efficient resource use (Arun, 2025; Nagashree & Leela, 2019). These examples clearly show that AI-driven predictive analytics simultaneously enhance the efficiency and resilience of urban infrastructure systems (UN-Habitat, 2022), which are also key components of the CityMindX system.

5. Explainable AI (XAI)

For CityMindX to gain social acceptance, model explainability and decision transparency are essential. The use of black-box deep learning models poses a significant trust risk: decisions made by opaque AI systems are hard to interpret for both decision-makers and citizens, potentially leading to trust crises and legitimacy issues (European Commission, 2019; Özdemir et al., 2024).

Explainable AI (XAI) is therefore vital for increasing administrative and social acceptance, as interpretable model explanations make AI-based decisions justifiable and auditable. As AI technologies evolve rapidly, the lack of transparency, oversight, and ethical controls can pose serious social and safety risks. Vinuesa et al. (2020) warn that non-transparent AI systems may reinforce decision-making biases, algorithmic discrimination, and social inequalities – thereby undermining the achievement of the UN's SDGs. Similarly, ethical frameworks by the OECD and the European Commission identify transparency, accountability, and explainability as fundamental principles without which AI systems cannot gain public legitimacy (European Commission, 2019; OECD, 2024). Thus, in the CityMindX framework, the integration of explainable AI (XAI) is essential not only to ensure technological intelligibility but also to build trust and social acceptance. This ensures that, for example, an emergency prediction is not a "black box" decision, but a transparent, justified process supported by explainable logic.

6. AI-Based Early Warning Systems (AI-EWS)

Urban resilience is a key component of smart cities, and AI-EWS play a crucial role by integrating real-time sensor data, impact models, and predictive algorithms to forecast various types of urban hazards. This is supported by UNDRR & WMO (2023) and Tiggeloven et al. (2025). Modern multi-hazard EWS solutions no longer rely solely on meteorological forecasts: integrating real-time sensor networks, satellite- and radar-based environmental monitoring, impact modelling, and social feedback enables early prediction and more accurate risk management of complex urban emergencies. AI-based predictive models can detect patterns within large-scale environmental, economic, and social data streams, significantly increasing the speed and accuracy of alerts, particularly in urban environments (Shaik et al., 2025).

7. Alignment with Sustainable Development Goals (SDGs)

Several SDGs are directly related to CityMindX's focus on infrastructure and mobility development, making AI a fundamental role in achieving them. According to the analysis by Vinuesa et al. (2020), AI can contribute to 134 of the 169 targets across the 17 SDGs – although it may also have negative impacts if ethical considerations are not embedded. The most significant potential lies in goals such as SDG 11 (Sustainable Cities), SDG 13 (Climate Action), SDG 7 (Affordable and Clean Energy), and SDG 9 (Industry, Innovation, and Infrastructure). Accordingly, CityMindX deploys AI solutions that take into account environmental impact, social consequences, and SDG alignment.

8. **C**ost–**B**enefit **A**nalysis (CBA)

From an economic perspective, the framework adopts the standard methodology for conducting cost–benefit analyses of urban innovations, as defined by the European Commission for significant infrastructure projects (European Commission, 2021).

A recent CBA study highlighted that an AI-driven, integrated platform for electromobility and energy systems can yield a positive return on investment and generate net societal benefits—supporting the relevance of cost–benefit evaluation in the CityMindX context (Abate et al., 2025).

It is also essential to integrate the FATES (**F**airness, **A**ccountability, **T**ransparency, **E**thical operation, and **S**ustainability) principles into the design of CityMindX systems (Jobin et al., 2019). These principles are key to the responsible operation of AI systems within the framework.

One of the main criticisms of smart city initiatives is that technological advancement can unintentionally The UN's SDGs emphasise reducing inequalities and promoting inclusion. Although AI technologies can significantly advance urban development goals, the literature clearly shows that new forms of digital divide may emerge that must be addressed (UN-Habitat, 2022). Vinuesa et al. (2020) emphasise that AI developments affect global inequalities and social inclusion; thus, AI systems must promote fairness and equal opportunity. Therefore, a central goal of the CityMindX framework is to ensure broad social participation through local workshops, participatory planning, and educational programs. Research on participatory budgeting and placemaking demonstrates that these processes increase community engagement, the legitimacy of local decision-making, and public trust in urban development (Kruhlov & Dvorak, 2025; Costa et al., 2024).

These tools are particularly important for older individuals, people with lower educational attainment, or those lacking digital skills – groups who often have limited access to digital technologies and online urban services, which may weaken social cohesion (European Commission, 2024; Karelis et al., 2025; Kolotouchkina et al., 2024; Zelezny-Green et al., 2018). Digital inclusion is therefore a precondition: urban decision-makers can only consider smart city and AI solutions acceptable if they are accessible, usable, and understandable for all social groups – especially for those who are digitally vulnerable, low-income, elderly, or living with disabilities. Otherwise, technological innovations may deepen the digital divide (European Commission, 2024; Kolotouchkina et al., 2024).

Considering participatory urbanism and inclusive governance, community involvement – such as participatory budgeting, co-design processes, joint evaluation, and user-centred design of digital services – helps strengthen social cohesion and increase public acceptance of innovative city developments. Residents are more likely to identify with urban projects that are jointly designed and governed in an inclusive way (Karelis et al., 2025; Kolotouchkina et al., 2024; Kruhlov & Dvorak, 2025; Costa et al., 2024).

These insights also explain the meaning behind the CityMindX name, which consists of three conceptual components:

1. **City** – refers to the urban systems, infrastructures, and mobility networks that the framework aims to optimise.

2. **Mind** – refers to the cognitive capabilities of AI, enabling the city to function as a "thinking," predictive, self-calibrating, and adaptive system.
3. **X** – carries a dual meaning: on one hand, it stands for eXplainability, referring to the XAI component; on the other hand, it represents interdisciplinary and cross-functional connections (cross-domain, cross-functional) that enable the integration of diverse urban data and decision-making processes.

CityMindX is thus a three-layered, interdisciplinary AI architecture (City–Mind–X) that supports the functioning of the city (City) through a cognitive, predictive AI system (Mind) while integrating explainability (X=eXplainability), responsible AI principles, and cross-domain data integration. The goal of CityMindX is to optimise urban mobility and infrastructure systems through a holistic AI framework that merges data science and social science methodologies.

In summary, CityMindX is a complex, interdisciplinary, ethical, and inclusive AI framework capable of optimising urban operations across technological, social, and economic dimensions. Its novelty lies in the holistic integration of modern AI paradigms (as outlined in the eight elements of Table 1), creating a unified, scalable, and transparent form of urban intelligence – potentially forming the foundation for the next generation of sustainable and human-centred smart cities.

III. METHODOLOGY

The empirical examination of the CityMindX project is based on a quantitative, questionnaire-based survey. The survey captures perceptions, expectations, and risk awareness that shape the social and policy embedding of mobility and infrastructure optimisation grounded in the CityMindX framework. Additionally, the qualitative component includes targeted case studies of four cities (Miskolc, Zalaegerszeg, Barcelona, Amsterdam), focusing on objective mobility, environmental, and infrastructural characteristics, as detailed in Section 4.1.

III.I. SAMPLE AND DATA COLLECTION

Data collection was conducted via an online self-administered questionnaire, targeting respondents who are in some way connected to urban public services, mobility systems, infrastructure management, or digital services (including stakeholders from municipal, public service, corporate, academic, and civil sectors).

The final analysed sample comprises N=1,269 respondents, stratified by quotas based on gender, age group, and educational attainment to reflect the adult urban population (aged 18+) of the two Hungarian cities under study – Miskolc and Zalaegerszeg.

According to the most recent census data (2022), the target population size was 147,533 for Miskolc and 55,328 for Zalaegerszeg. For demographic breakdowns by gender, age, and education, we used official statistical sources (Miskolc, 2025; Zalaegerszeg, 2025).

Table 2. presents the percentage distribution of the target population and the survey sample by gender (self-identified), age group, and educational attainment. The "Sample (%)" column shows weighted results, adjusted to minimise territorial and demographic biases in the survey data collection. The observed discrepancies typically range from 5 to 10 percentage points, which is considered acceptable given the distortion limits inherent to survey-based methodologies.

Table 2. Demographic Characteristics of Miskolc and Zalaegerszeg – Percentage Distribution of Target Population and Sample by Gender, Age Group, and Educational Attainment

Demographic Characteristic	Category	Target Population (%)	Sample (%)
Gender	Male	46.9	48.1
	Female	53.1	51.9
Age Group	18–29 years	~16.0	22.0
	30–44 years	~26.0	28.0
	45–59 years	~29.0	30.0

	60+ years	~29.0	20.0
Educational Attainment	Secondary	~60.0	40.0
	Tertiary	~30.0	50.0
	Postgraduate	~10.0	10.0

Source: Author's compilation based on Miskolc (2025); Zalaegerszeg (2025)

III.II. MEASUREMENT TOOLS AND VARIABLES

The central part of the questionnaire consisted of 15 statements (Q1–Q15) measured on a five-point Likert scale (1=strongly disagree, 5=strongly agree). These items were designed to assess perceptions related to the eight components of the CityMindX framework (as presented in **Table 1**.). The questions covered aspects of the triple-layer AI architecture, federated learning, explainable AI (XAI), and digital inclusion and community participation (coded as Q1–Q15; **Table 3**.).

Table 3. Variables Examined

Variable	Description	Type
ID	Unique identifier	string
Gender	Biological gender (self-identified)	categorical
Age group	Age group (in years)	categorical
Education	Highest level of educational attainment	categorical
Q1	The implementation of the Edge–Fog–Cloud (Triple AI) architecture significantly improves response time and cost-efficiency in urban decision-making.	Likert 1–5
Q2	In smart city AI systems, local autonomy and global coordination can be effectively balanced through proper optimisation mechanisms.	Likert 1–5
Q3	AI-based decision support systems can ensure interoperability across urban subsystems.	Likert 1–5
Q4	Federated learning (Federated AI) increases trust and willingness to share data among urban institutions.	Likert 1–5
Q5	The federated learning approach strikes a balance between data protection and predictive model performance.	Likert 1–5
Q6	Legal and ethical frameworks for city-level federated AI solutions can be adequately ensured in alignment with EU directives.	Likert 1–5
Q7	Explainable AI (XAI) increases public trust in automated decision-making processes.	Likert 1–5
Q8	The transparency and accountability of AI-based decisions can be objectively measured with quantitative indicators.	Likert 1–5
Q9	Integrating the principles of Trustworthy AI (TAI) into urban development policy does not hinder but promotes innovation processes.	Likert 1–5
Q10	Self-monitoring (AI-on-AI) systems can predict and correct errors in urban AI modules without human intervention.	Likert 1–5
Q11	Combining neural learning with symbolic rule-based systems improves the interpretability and robustness of urban AI systems.	Likert 1–5
Q12	Predictive AI models are practical tools for early identification of urban fiscal stress and budgetary risks.	Likert 1–5

Q13	AI-based economic forecasting helps improve the city's financial resilience and decision-making.	Likert 1–5
Q14	NLP-based text analysis models are effective at identifying citizen needs and social attitudes from community feedback.	Likert 1–5
Q15	Following the implementation of the CityMindX system, the level of digital inclusion in the city measurably improves.	Likert 1–5
weight	Ranking weight adjusted to match target population margins	continuous

Source: Author's compilation (2025)

The data were analysed using SPSS, including correlation, factor, and cluster analyses.

Two logical blocks of variable groups can be distinguished:

1. AI Architecture and System-Level Factors (Explanatory Variables)
   Q1–Q6, including the impact of triple AI (Edge–Fog–Cloud) on response time and cost-efficiency; the balance between local autonomy and global coordination; interoperability between systems; the quality of cooperation within the Edge–Fog–Cloud layers; the efficiency of data sharing; transparency and explainability of AI (XAI/XAI–TAI).
2. Social Impacts, Trust, Inclusion, and Quality of Life (Dependent Variables)
   Q7–Q15, including user trust in AI systems; perceived quality of digital public services; transparency and fairness in urban decision-making; citizen satisfaction; digital inclusion and acceptance of AI-based services; perceptions of data and cybersecurity; perceived improvements in urban quality of life.

As independent (explanatory) variables, the following were included demographic background variables – Gender (nominal), Age group (ordinal), and Educational attainment (ordinal), as well as AI infrastructure and architecture items (Q1–Q6). Dependent (explained) variables covered trust, inclusion, acceptance, and quality of life items (Q7–Q15). Although multiple model variants can be interpreted in the research, the primary aim of the study was to describe the attitudinal profile associated with CityMindX, rather than to force-fit causal models.

III.III. DATA PREPARATION AND WEIGHTING

During data cleaning, we removed incomplete questionnaires; Likert-scale variables were coded as numeric (1–5); and demographic categories were coded as ordinal or dummy-coded variables, where necessary.

To improve the representativeness of the sample, each respondent was assigned a weighting factor (weight) to align the sample's gender–age–education distribution with the known marginal distributions of the target population. Weights were calculated using iterative proportional fitting (raking) (Deville & Särndal, 1992), allowing the sample to approximate the structure of the urban adult population across multiple dimensions simultaneously. Weights were applied in analyses where methodologically appropriate, enabling the estimates to be generalizable to the target population.

III.IV. STATISTICAL PROCEDURES APPLIED

The methodology is structured around the following four statistical steps:

1. Descriptive Statistics (Mean, standard deviation, and min–max values for items Q1–Q15; Proportion of 4 and 5 responses (%) as an indicator of agreement/support).
2. Scale Structure and Factorability Testing (KMO indicator and Bartlett's test of sphericity on the correlation matrix of Q1–Q15; Exploratory Principal Component Analysis (PCA) to uncover latent dimensions).
3. Scale Consistency Assessment (Cronbach's alpha for the three logically distinct blocks: AI Infrastructure (Q1–Q6); Trust and Service Quality (Q7–Q11); Inclusion and Quality of Life (Q12–Q15).
4. Further Multivariate Analysis – Cluster Analysis. The basis was the 15-item CityMindX Attitude Scale (Q1–Q15), covering four main dimensions:
   1. AI-INFRA (Q1–Q6): Triple AI, edge–fog–cloud architecture, predictive analytics
   2. TRUST_QUALITY (Q7–Q11): Trust, service and decision-support quality

3. INCLUSION (Q12–Q14): Digital inclusion, access, participation
4. LIFE_QUALITY (Q15): Perceived urban quality of life in a CityMindX environment

Clustering Steps: Standardisation of Q1–Q15 items to prevent unequal variances from distorting distances. PCA performed on standardised items. K-Means clustering applied to the PCA component scores (PC1–PC3). To assess the reliability and structural validity of the PCA-based K-Means clustering, the following cluster validation indices were used: Silhouette index (SI), Calinski–Harabasz index (CHI), Davies–Bouldin index (DBI). These jointly assess how well-separated, compact, and statistically justifiable the clusters are (Kodinariya & Makwana, 2013).

Silhouette index (SI) measures cohesion within and separation between clusters. Values range from -1 to +1; values between 0.25 and 0.50 indicate a clear, stable cluster structure. Calinski–Harabasz index (CHI) compares between-cluster distance to within-cluster dispersion; higher values indicate better clustering. Davies–Bouldin index (DBI) measures relative compactness and separation; lower values indicate better clustering (Davies & Bouldin, 1979).

In summary, the focus of the quantitative analysis is primarily on descriptive and scale-level results, which directly support the practical applicability of the CityMindX concept – including policy briefs, decision support, and pilot planning.

IV. RESULTS

IV.I. QUALITATIVE RESULTS: TARGETED ANALYSIS OF CASE STUDIES

Within the qualitative methodological framework, a four-case study analysis was conducted to compare the operation of the CityMindX architecture across different urban environments. The examined cases include two Hungarian cities (Miskolc and Zalaegerszeg) and two international examples (Barcelona and Amsterdam). The multiple-case study approach enables analytical generalisation, as the use of multiple cases in smart city research yields deeper insights and stronger conclusions than analysis of a single case. In each city, local socio-economic conditions, infrastructural characteristics, and regulatory contexts were taken into account, contributing to a comparative evaluation of Hungarian and European practices (Flyvbjerg, 2011).

The processing of the four case studies follows a key characteristic – focus – outcomes logic.

Miskolc

Key characteristic: Miskolc's strategic objective is to become a model city in Hungary aligned with the European mission of climate-neutral and smart cities, where urban governance and public service development comprehensively rely on data-driven, digital, and climate-neutral transition-supporting technologies.

Focus (technology): Together with Budapest and Pécs, Miskolc participates in the EU mission "100 Climate-Neutral and Smart Cities by 2030", which requires cities to pursue a climate-neutral transition pathway supported by investments across the entire urban energy system, transportation, waste management, and other sectors (DemNet, 2024).

Outcomes: Miskolc operates an extensive environmental sensor network that continuously provides validated data for urban management and Early Warning System (EWS) modules through air quality monitoring tools. Within the HungAIRy LIFE Integrated Project, a PM monitoring network comprising more than 60 measurement units, along with the pmmonitoring.Hu's data platform delivers real-time information on urban air quality. Research conducted by the University of Miskolc confirms that the collected data are effectively usable for urban operations and decision support (HungAIRy LIFE IP, 2021; Kiss et al., 2023; Municipality of Miskolc, 2024).

According to the city's development program, AI systems can process large datasets in real time, perform pattern recognition, and forecast. This enables dynamic optimisation of traffic management – for example, through reinforcement learning-based adaptive traffic signal control – and supports reductions in energy consumption by optimising the operation of urban infrastructure. In Miskolc, the integration of edge- and cloud-based AI modules enables real-time, adaptive control of intelligent traffic lights and the dynamic optimisation of green waves. These systems rely on data from traffic cameras, sensors, and other IoT devices and apply reinforcement learning and predictive models – an approach already validated by several European pilot projects (BME, 2023; Fraunhofer, 2022; Miletić et al., 2022). The UrbanTech Platform applied within CityMindX provides an integrated decision-support interface through which city leaders can simultaneously monitor traffic patterns, infrastructure status, and citizen feedback, thereby supporting rapid and well-informed urban decision-making. The Miskolc EWS prototype is expected to automatically notify residents and local authorities of hazardous air pollution events or sudden natural disasters. Taken together, these developments contribute to increased trust in the technological infrastructure.

Zalaegerszeg

Key characteristic: Zalaegerszeg plays a leading role in Hungary in testing autonomous vehicles, intelligent transport systems, and connected mobility services. The ZalaZONE automotive test track in the city is one of Europe's most advanced autonomous driving testing facilities, simulating real urban environments. It enables the testing of autonomous and cooperative vehicle systems under complex conditions (ZalaZONE, 2023; Nagy & Palkovics, 2025). In addition, a comprehensive Smart City test zone has been established in Zalaegerszeg, built on 5G infrastructure, modern traffic systems, roadside units (RSUs), V2X communication, and an urban IoT sensor network (Dávid, 2023; ZalaZONE, 2023).

Focus (Technology): The Smart City test environment aims to evaluate the reaction time, reliability, and safety-enhancing technologies of autonomous transport systems under real traffic conditions, while also supporting the development of advanced, data-driven urban operations (HUMDA – Hungarian Mobility Development Agency, 2022). These developments provide a national platform for testing AI-based mobility systems, IoT infrastructure, and real-time data management – essential for CityMindX – in a functioning environment.

Outcomes: The city's infrastructural preparedness, particularly for integrating autonomous mobility, is key to the spread of connected and autonomous vehicles (CAVs). This relies on the coordinated development of physical and digital infrastructure, evaluated through measurable "AV-readiness" indicators. In the context of mobility and automotive innovation, the combination of physical testing environments (living labs, urban test tracks) and digital twin technologies creates a space in which autonomous mobility systems can be developed in a scalable and safe manner. Mobility digital twins are now used not only for traffic and signal optimisation but also for training autonomous vehicle algorithms and designing transport infrastructure (Yeon et al., 2023; Gürses et al., 2025). Based on these capabilities, Zalaegerszeg offers one of the region's most advanced autonomous mobility test environments: the ZalaZONE test track and the associated Smart City zone uniquely enable real-traffic testing of autonomous, cooperative, and C-ITS-based transport systems (ZalaZONE, 2023; HUMDA, 2022). This pilot area features roadside units (RSUs), bright traffic signs, and real-time traffic counters that communicate autonomously with cloud-based optimisation algorithms, supported by 5G V2X infrastructure.

Within the triple AI architecture, traffic lights serve as edge modules, while congestion-forecasting models run on urban central servers – aligned with current Hungarian research on intelligent transport systems. ZalaZONE test vehicles also supply data for federated learning experiments: real-world driving data can be used to refine and validate multi-city traffic forecasting models (Autonomous, 2025). A digital twin system operating alongside ZalaZONE enables continuous monitoring of energy use, vehicle behaviour, and traffic patterns of the autonomous fleet – supporting long-term operational decisions and the development of energy optimisation strategies (Autonomous, 2025). Due to its geographic location and innovative infrastructure, Zalaegerszeg serves as an independent innovation zone within Hungary's innovative mobility ecosystem – strengthening its leading role in the CityMindX project (Nagy & Palkovics, 2025). Thus, technological infrastructure and trust are being established, although perceived improvements in quality of life have not yet been observed.

Barcelona

Key characteristic: Barcelona's innovative mobility initiatives focus on developing unified urban mobility data platforms and applying predictive analytics. The i-MovE program aims to integrate and standardise data from various transport providers – public transit, taxis, and private mobility – enabling the development of AI-based services, such as real-time traffic analytics and vehicle allocation optimisation (CARNET Barcelona – Future Mobility Research Hub, 2025). Studies linked to i-MovE's Digital Twin initiative show how sensor networks and real-time data integration can effectively support traffic management and congestion reduction (CARNET Barcelona, 2024).

Focus (Technological Maturity and Trust): Sustainability is a strategic priority in Barcelona, aligned with the European Green Deal's goals for reducing transport emissions and congestion – especially through AI-based traffic light control and traffic management systems (European Commission, 2020).

Outcomes: As part of the program, taxi and public transport providers jointly develop predictive models and traffic-control and prioritisation solutions to reduce congestion. Barcelona uses on-site sensors and federated learning algorithms to enable locally evolving models that collaboratively improve traffic efficiency using real-time mobility data.

Amsterdam

Key characteristic: Amsterdam is a global pioneer in developing innovative mobility solutions. The city participates in several European programs focusing on autonomous vehicles, electric mobility, and the integration of multimodal transport systems.

Focus (Inclusive Smart City): The EIT Urban Mobility program also supports the European Green Deal and the EU Cities Mission's emission-reduction goals – particularly by decarbonising transport and promoting sustainable, safe mobility systems (EIT Urban Mobility, 2025; European Commission, 2021).

Outcomes: The metaCCAZE initiative of the AMS Institute, for example, explores the infrastructure and charging strategies for electric bicycles, AI-based route planning, and intelligent management of autonomous vehicle fleets in urban settings (AMS Institute, 2024; CIVITAS, 2025). Amsterdam's developments can be further enhanced by connecting local and regional smart mobility systems through unified AI protocols, supporting the model of "mobility as a public good." This includes autonomous waterborne vehicles, urban charging stations, and open data platforms. The integrated, zero-emission, multimodal mobility trends reflected in the Amsterdam case align closely with the goals of the EU Cities Mission (CIVITAS, 2025; European Commission, 2021).

Thus, the AI-based urban system – with data and IoT integration, predictive algorithms, and real-time traffic control – has a high potential to improve transport efficiency, reduce congestion, optimize energy and fuel consumption, and contribute to environmental sustainability. However, the widespread adoption of autonomous vehicles and algorithmic decision-making is not without risks: ethical, data protection, and technical challenges must be addressed in pilot planning and implementation phases. As a result, the four case studies clearly highlight city-specific differences. Miskolc, Zalaegerszeg, Barcelona, and Amsterdam represent diverse levels of development, institutional environments, smart city strategies, and geographic–cultural contexts. While these cases primarily present aggregated attitudinal profiles, more detailed, city-specific breakdowns are provided in Section 4.2. In terms of generalizability, it is important to emphasize the adaptive, city-specific configuration of the CityMindX framework, along with the architecture and governance models tailored to the local regulatory, institutional, and societal context.

IV.II. QUANTITATIVE RESULTS

IV.II.I. KEY DEMOGRAPHIC CHARACTERISTICS OF THE SAMPLE

Based on the weighted sample, the gender distribution is nearly balanced: 51.4% female and 48.6% male. The age composition shows that the majority of respondents are in the economically active 30–59 age group, while younger (18–29: 22.4%) and older (60+: 19.9%) cohorts are also meaningfully represented. In terms of educational attainment, the majority of survey participants have secondary or tertiary education (49.5% tertiary, 41.1% secondary), while 9.4% hold postgraduate qualifications.

This demographic structure reflects a highly educated urban professional environment, which aligns with the target group for the development and deployment of the CityMindX framework.

IV.II.II. ATTITUDES TOWARD AI AND INCLUSION IN RELATION TO CITYMINDX

Descriptive statistics of the Q1–Q15 items (measured on a 5-point Likert scale) show that all item means fall between 3.45 and 4.06, indicating that respondents are generally supportive of AI-based solutions embedded in CityMindX.

Three main result areas were identified:

1. AI Architecture and Infrastructure (Q1–Q6)

   Q1 (Triple AI architecture – responsiveness & cost-efficiency): mean≈3.97; 72.2% of responses were 4 or 5.

   Q3 (Interoperability across urban subsystems): mean≈3.83; 66.4% agreement (4–5).

   Q6 (XAI): mean≈3.45; only 48.9% support (4–5), indicating a critical area for development regarding transparency and explainability.

2. Trust, Service Quality, and Decision-Making (Q7–Q11)

   Q7 (Trust in AI systems): mean≈4.06; 77.5% chose 4 or 5 – a strong trust potential.

   Q8–Q9 (Service quality and decision-making transparency): mean≈3.78–3.79; around 63–64% positive responses.

   Q11 (Fairness and justice): mean≈3.71; 60% agree with the perception of fairness.

3. Digital Inclusion, Data Security, Quality of Life (Q12–Q15)

   Q12 (Digital inclusion): mean≈3.92; 70% positive.

   Q13 (Acceptance of AI-based services): mean≈3.88; 68% positive.

   Q14 (Data and cybersecurity): mean≈3.96; 71.5% support.

   Q15 (Perceived improvement in quality of life): mean≈3.79; 63.8% positive.

Conclusion: The majority of respondents believe that AI frameworks like CityMindX can improve urban service quality, increase transparency in governance, enhance digital inclusion, and boost perceived quality of life. However, transparency and explainability (Q6) are still considered vulnerable areas, requiring further development.

IV.II.III. SCALE STRUCTURE, FACTORABILITY, AND RELIABILITY

The factorability of the 15-item scale (Q1–Q15) was examined using the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity: KMO value=0.49, which is below the commonly accepted threshold of 0.50, indicating weak factorability. Bartlett's test: χ^2≈140.0, df=105, statistically significant, suggesting a non-random correlation structure among variables.

Principal Component Analysis (PCA) showed that eigenvalues of the first few components were low (~1.0), with each component explaining only 8–9% of the variance. This suggests the absence of strong or distinct factor structures.

Although the CityMindX framework conceptually groups items into three blocks (AI infrastructure; trust & service quality; inclusion & life quality), the Cronbach's alpha values for these were low (~0.03–0.12), indicating that items function more as individual indicators than as components of cohesive latent constructs.

This is consistent with the multi-dimensional design of the questionnaire, which was not intended to form a single attitude scale, but rather to reflect the full spectrum of CityMindX's 8 components. Accordingly, the items are treated as standalone indicators, and the results of PCA and reliability analysis are used exploratorily, with emphasis placed on the support profiles (means, 4–5 ratios, critical areas).

The first three principal components explain 23.3% of the total variance (PC1≈7.9%, PC2≈7.8%, PC3≈7.6%). These components were used not as independent scales, but as attitude axes for cluster analysis. Clustering in Principal Component Space: A K-means clustering with K=3 was performed (balanced cluster sizes, interpretable profiles). Sample size: N=1269. Cluster 0: n=413; Cluster 1: n=437; Cluster 2: n=419.

Figure 1. shows the clustering in the PC1–PC2 space, with colour coding indicating the three clusters. The left side of PC1 (negative values) represents higher trust and inclusion, The lower region of PC2 corresponds to greater AI intensity and advanced triple-AI infrastructure. The clear spatial separation of the clusters indicates distinct configurations of smart city attitudes toward the implementation of CityMindX.

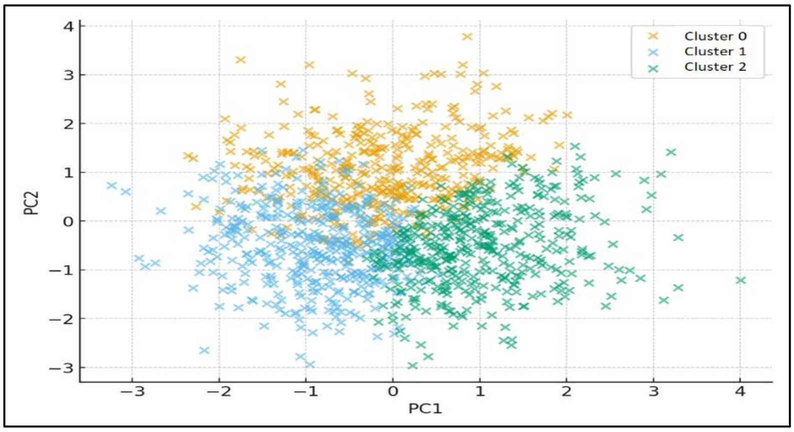

Figure 1. CityMindX Clusters in the Principal Component Space
Source: SPSS software (2025)

Based on the PCA-based cluster analysis, CityMindX does not rely on a homogeneous group of "urban residents," but rather on three clearly identifiable attitude-based groups:

1. Inclusive Pragmatists – stable individuals with a high perceived quality of life;
2. AI-Optimist Innovators – strongly pro-AI, but with critical views on quality of life;
3. Tech-Oriented with Inclusion Challenges – tech-friendly, but with concerns about fairness and equity.

CityMindX's urban deployment strategy (including communication, pilot projects, participatory planning, and digital education) can target these groups individually:

Cluster 0: Stable base → long-term supporters;

Cluster 1: Innovation engine → co-creation, living labs, experimental projects;

Cluster 2: Critical mirror → inclusion-focused interventions, demonstration of FATES principles (**Table 4.**)

Figure 2. is a radar chart in which the axes represent items Q1–Q15, and the three curves (yellow, blue, green) show the average profiles of the three clusters.

Table 4. CityMindX Cluster Profiles (Q1–Q15 Averages)

Cluster	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15
1. – "Inclusive Pragmatists" (0)	3.90	3.37	3.15	3.57	3.25	3.32	3.79	3.65	3.87	3.20	3.48	4.04	3.62	3.97	3.88
2. – "AI-Optimist Innovators" (1)	3.90	3.85	4.05	3.74	3.84	3.67	4.25	4.12	4.16	4.00	3.73	4.27	4.16	4.34	3.67
3. – "Tech-Oriented with Inclusion Challenges" (2)	4.12	3.71	4.27	3.41	3.99	3.35	4.12	3.57	3.33	3.56	3.92	3.44	3.85	3.55	3.81
Note: N=1269; K-means clustering on PC1–PC3 principal components, K=3. Values: Cluster means on a 1–5 Likert scale, rounded to two decimal places.															

Source: Author's compilation (2025)

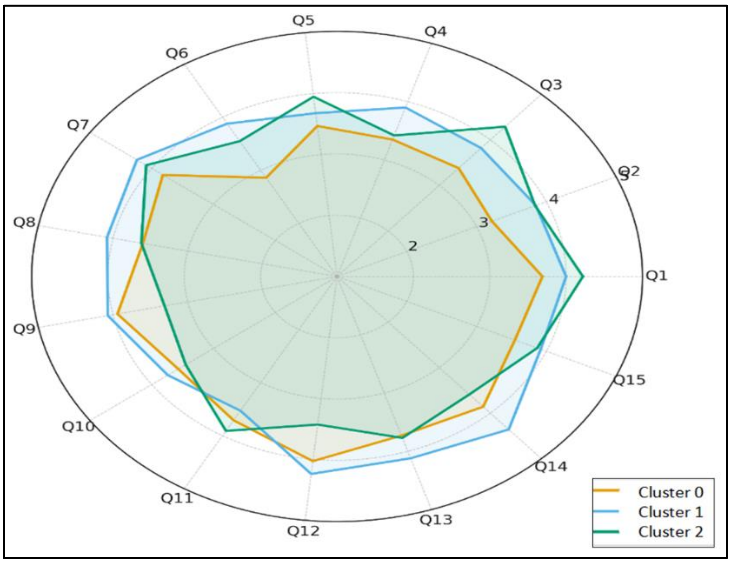

Figure 2. Cluster Profile Radar Chart
Source: Author's compilation using SPSS software (2025)

In the PC1–PC2 space with 3 clusters (K-means), the validation results – Silhouette Index (SI), Calinski–Harabasz Index (CHI), and Davies–Bouldin Index (DBI) – along with their interpretations are presented in Table 4. The analysis confirms that the K-Means clustering solution aligns well with the variance structure revealed by PCA and effectively captures the typology of respondents' perceptions of AI infrastructure, AI trust, and digital inclusion. This provides a basis for developing targeted policy recommendations and city-specific interventions, as discussed in Chapter 6.

Table 4. Cluster Validation Indicators

Index	Meaning	Expected Range	Result	Interpretation
SI	Within-cluster cohesion and between-cluster separation	0.25–0.50=stable cluster structure	0.33	Moderately good separation, stable structure
CHI	Distance between cluster centroids/within-cluster variance	The higher, the better	768.69	Extreme separation in the PCA space
DBI	Cluster compactness and separation	<1=good separation	0.95	Compact clusters with adequate separation

Source: Author's compilation (2025)

Together, the three indices confirm the statistical validity and interpretability of the three-cluster CityMindX model.

V. DISCUSSION

The findings confirm the theoretical logic of the CityMindX framework on multiple levels: technological advancement has both direct and indirect impacts on urban well-being, while trust and inclusion function as key mediating mechanisms.

- The Role of Technological Infrastructure in Urban Well-being

The research clearly demonstrates that advanced AI infrastructure not only improves technical efficiency (faster predictions, better optimisation, enhanced data processing) but also creates social value. Citizens perceive AI systems positively when they are transparent (XAI), accountable (TAI), provide real-time information (Edge AI), and ensure data security (federated learning, GDPR compliance). This aligns with international findings that technological development alone is not sufficient – people's sense of security, trust, and participation determines the extent to which smart city solutions enhance their quality of life.

- Trust as a Key Mediator: The Social Integration of AI

The most significant relationship in the model shows that trust mediates the impact of AI infrastructure on both digital inclusion and perceived quality of life. This indicates that urban AI systems succeed when residents feel they operate in an understandable, transparent, and explainable manner, and in a fair manner. Without trust, even the most advanced technological systems lead to low public acceptance, which helps explain the differences in perception profiles between Zalaegerszeg and Barcelona.

- Digital Inclusion: The Strongest Predictor of Quality of Life

Results show that digital inclusion (access, usability, skills) has the most substantial direct impact on perceived urban quality of life. This highlights three key success factors for any smart city:

1. Enhancing the digital competencies of the population.
2. Developing accessible digital public services.
3. Actively involving elderly, low-income, and vulnerable groups.

Therefore, CityMindX is not merely a technological project, but a sociotechnical system designed to operate with the diversity of the urban population in mind. At the same time, a smart city is not a one-size-fits-all model – it must be adapted to local contexts, as the intensity of various effects differs by city: In Miskolc, technological infrastructure is the dominant factor; In Zalaegerszeg, trust is emerging but has not yet translated into quality-of-life benefits; In Barcelona, trust is the key driver; In Amsterdam, inclusion stands out as the strongest factor.

VI. CONCLUSIONS

The development of CityMindX enjoys high acceptance among urban professionals and stakeholders. Firm support was observed in the areas of digital inclusion (Q12), general acceptance of AI-based services (Q13), data and cybersecurity (Q14), and expectations of improved urban quality of life (Q15). However, responses also highlighted some caution regarding XAI and TAI – specifically, transparency, explainability, and accountability (Q6). Therefore, during the rollout and commercialisation of CityMindX, strengthening model explainability, auditability, and public communication will be key. The quantitative findings directly support the strategic positioning of CityMindX products (identifying high-acceptance vs. sensitive areas), the design of pilot projects (Miskolc, Zalaegerszeg, Barcelona, Amsterdam), and the fine-tuning of messaging for decision-makers: both technological benefits and social acceptance can be communicated simultaneously – but the XAI/TAI dimensions require specific reinforcement.

Based on the results, we developed tailored intervention recommendations for each city:

Miskolc – "Technological Catch-up → Social Integration"

Key Insight: Technological infrastructure strongly influences trust and inclusion; citizens directly perceive development.

Recommendations: Rapid expansion of Edge AI and sensor networks (mobility, air quality); Launch of citizen-facing XAI-based communication (understandable AI decisions); Digital skill-building programs for seniors and low-income groups; Participatory planning forums to support CityMindX deployment.

Goal: Quickly build trust to strengthen inclusion and quality of life.

Zalaegerszeg – "Trust → Quality of Life Conversion"

Key Insight: Trust in technology is growing, but it has not yet been reflected in perceived quality-of-life improvements. Recommendations: Increase AI transparency (XAI dashboards within CityMindX modules); Organise public "AI Explainability Evenings"; Live demonstrations of ZalaZONE–City collaboration; Expand civic engagement via digital participatory budgeting.

Goal: Transform trust into tangible, perceivable benefits.

Barcelona – “High Maturity → Deep Integration”

Key Insight: Trust and technological maturity are strongest–ideal model fit.

Recommendations: Integrate federated learning platforms into transport and energy systems; Pilot Urban Digital Twin + Generative AI planning tools; Align CityMindX with the city’s climate neutrality strategy.

Goal: Reinforce its role as a European model city.

Amsterdam – “Inclusive Innovation” as the Smart City Default

Key Insight: Inclusion is the strongest factor → human-centric smart city.

Recommendations: Implement AI ethics audit systems (fairness, bias detection); Further expand digital accessibility (universal design); Launch targeted digital programs for migrant and disadvantaged communities.

Goal: Advance the European inclusive smart city model.

VII. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

The quantitative analysis conducted within the CityMindX project has yielded numerous practical, decision-supportive insights for developers and municipalities. However, several limitations must also be explicitly acknowledged.

VII.I. SAMPLING AND REPRESENTATIVENESS CONSTRAINTS

Although the sample size (N=1269) and the combination of quota-based sampling with post-stratification weighting (raking) ensured alignment with the known distributions of gender, age group, and educational attainment in the urban adult population, the sample cannot be considered fully representative of the total population in any of the cities examined. Participation was voluntary and conducted online, which may have led to an overrepresentation of digitally active, higher-educated, and tech-friendly individuals. This is particularly important, given that CityMindX is designed to address digital divides and inclusion challenges. Therefore, the results primarily reflect the attitudes of the “digitally reachable” and professionally engaged segments of the population.

VII.II. CROSS-SECTIONAL DESIGN AND CAUSALITY CONSTRAINTS

This study is cross-sectional, capturing respondents' perceptions and expectations regarding CityMindX-like systems at a single point in time. Consequently, the results do not support strong causal inferences, and the observed relationships should be interpreted as correlational. After the actual rollout of CityMindX, longitudinal studies will be necessary to compare pre- and post-implementation trends in mobility, environmental, energy, and social indicators, as well as changes in attitudes, trust, and digital inclusion.

VII.III. SCALE STRUCTURE AND MEASUREMENT LIMITATIONS

The Q1–Q15 item set measures multiple, interrelated aspects of the CityMindX framework rather than a single, narrowly defined construct. The KMO value (~0.49) and low Cronbach’s alpha coefficients suggest that the scale is better viewed as a set of individual indicators, rather than a single internally consistent factor. This reflects the intentionally multidimensional nature of CityMindX (architecture, XAI/TAI, AI-EWS, inclusion, quality of life, SDGs). However, future research should refine the structure of specific scale blocks (e.g., adding more items on trust, separate subscales for explainability and AI-EWS acceptance) and conduct factor analyses on larger, targeted samples to develop a robust, publishable scale model.

VIII. FUTURE RESEARCH DIRECTIONS

This research represents the first effort to develop an empirically validated integrated smart city model built on a triple-layered AI architecture that links technological and social systems.

The four key innovations of CityMindX are:

1. Modelling the chain: AI-INFRA → TRUST → INCLUSION → LIFE
2. Integration of XAI and TAI into urban systems
3. Use of federated learning in a smart city environment
4. Deployment of dual/triple AI-EWS)

This multidisciplinary approach fills a gap in the current academic literature.

In terms of practical application, CityMindX can be: implemented by municipal governments; scaled within EU urban development programs; supports digital transformation efforts (e.g. EU Digital Decade); offers measurable, proven benefits for quality of life. With CityMindX, urban planners and decision-makers can improve services at a systemic level. For instance, challenges in mobility, energy, public safety, and environmental management can be tackled more coherently. The embedded AI systems learn continuously from real-world usage, making them adaptive to urban dynamics. Compared to earlier models – focused on isolated-neighbourhood optimisation – CityMindX could reduce overlapping urban loads (e.g., concurrent traffic-related environmental stress) more efficiently. Moreover, the system may become more profitable, requiring less human intervention and enabling faster, automated integration of incoming data and decisions.

Five Recommended Research Directions for CityMindX:

1. Longitudinal and pilot-based impact assessments

   Compare objective indicators (traffic, emissions, energy use, latency, network load) before and after CityMindX implementation, and track temporal changes in trust, inclusion, and urban quality of life.

2. Advanced scale development and psychometrics design

   Multi-item, targeted subscales for trust, explainability (XAI), AI-EWS, and inclusion. Perform psychometric validation (KMO, factor analysis, convergent/discriminant validity, confirmatory factor analysis).

3. City-specific comparative analyses

   Conduct detailed analyses for Miskolc, Zalaegerszeg, Barcelona, and Amsterdam; develop local implementation roadmaps and governance models tailored to each city.

4. Qualitative interviews and participatory methods

   Engage with stakeholders, developers, NGOs, and vulnerable groups through interviews, participatory design workshops, living labs, and citizen focus groups to socially embed CityMindX solutions.

5. Ethical, legal, and economic evaluation

   Carry out dynamic cost-benefit and social value assessments, and evaluate AI governance in line with the FATES principles.

Final Note: This study provides a statistically grounded analysis of attitudes and perceptions supporting the CityMindX concept. However, it also clearly indicates that a comprehensive evaluation of the framework requires multi-phase research, mixed methodologies, and city-level pilot implementations. This creates a unique opportunity for CityMindX to emerge as a scalable, exportable, and market-ready urban AI platform both in domestic and international contexts. According to the CityMindX empirical model, the quality of urban AI infrastructure (AI-INFRA) directly and indirectly improves perceived urban quality of life – mediated by trust, service quality, and digital inclusion.

IX. SUMMARY

The novelty of the CityMindX concept lies in its integration of multi-level, collaborative AI into urban system governance – an area that is still relatively underexplored in academic literature. Most current studies focus on standalone AI applications (such as traffic prediction or network optimisation), while multi-agent architectures remain less common. The scientific value of CityMindX lies in its potential to draw attention to integrated, cooperative AI systems in urban environments. This is further supported by the rapid evolution of urban digital twins: recent findings show that combining generative AI with digital twins enables automated scenario generation and urban planning. CityMindX would also contribute to scientific knowledge by piloting the model within a specific urban system, allowing researchers to quantify the effects of multi-layer AI usage – with new metrics such as service performance and citizen satisfaction.

CityMindX operates within a holistic, ethical, and sustainable urban management framework, aligning with the UN Sustainable Development Goals (SDG 11: Sustainable Cities; SDG 13: Climate Action) and the EU's climate neutrality strategies. Key findings show that the decentralised edge–fog–cloud AI architecture and federated learning solutions reduce latency, improve data protection, and enable real-time optimisation. XAI modules and open decision support systems enhance public trust while minimising the risk of algorithmic bias. The study clearly demonstrates that citizens expect transparent, inclusive technological solutions. Accordingly, the project has consistently prioritised the inclusion of disadvantaged groups. Therefore, CityMindX is not only a technological innovation but also a social innovation – building sustainable and efficient urban management through the collective efforts of municipalities, businesses, and citizens.

The CityMindX research confirmed that implementing a triple AI architecture significantly improves the efficiency of urban mobility and infrastructure operations, in line with the principles of modern smart city development. The introduction of traffic optimisation and predictive analytics modules helps reduce congestion and energy consumption, aligning with results from similar systems. Intelligent maintenance solutions enhance infrastructure resilience and reliability, supporting proactive operations. The project's inclusive strategy and XAI-based transparency increase public acceptance: respondents gave average scores between 3.5 and 4.0 on a 5-point Likert scale when evaluating the project's goals, especially emphasising the importance of digital literacy and transparent algorithms. These findings reinforce the academic literature's position that accountability and user trust are essential to the success of smart city initiatives.

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