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Urban Computing: A Holistic Framework Tailored for 3D Geosimulation and Enlightened Prospective Analysis

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Abstract

Urban Computing (UC) stands as an interdisciplinary field where urban challenges are examined and, where applicable, addressed through cutting-edge computing technologies. The swift pace of urbanization has brought about significant improvements in many aspects of people's lives, but it has also given rise to substantial challenges like traffic congestion, energy consumption, pollution, soil artificialization, and heat islands. In response, Urban Computing seeks to confront these issues by leveraging the data generated in cities, facilitated by urban sensing, data management, data analytics, and service provision. This iterative process aims for unobtrusive and continuous enhancements in the quality of life, city operations, and environmental conditions. This paper introduces a comprehensive framework tailored for Urban Computing, specifically attuned to the requirements of 3D geosimulation and informed prospective analysis. Given the dynamic evolution of urban environments, the demand for sophisticated computational tools has become increasingly imperative. The proposed framework integrates cutting-edge technologies to address the intricacies associated with urban dynamics, providing a foundational basis for well-informed decision-making. Encompassing components for data acquisition, processing, modeling, simulation, and analysis, the framework underscores the synergy among these elements, promoting a holistic understanding of urban phenomena.

Keywords: Urban Sensing; Urban Data Analytics; Explainability; Smart Cities; Sustainable Development Goals; Machine Learning

Introduction

Urban areas are dynamic ecosystems shaped by complex interactions between social, economic, and environmental factors [1-6]. As global urbanization accelerates, understanding and managing these complexities become imperative for sustainable development. Urban Computing, a multidisciplinary field at the intersection of computer science, data science, and urban planning, has emerged as a powerful paradigm for comprehending urban dynamics. In recent years, cities worldwide have increasingly embraced a technocentric paradigm to realize the concept of the smart city, employing advanced technologies within urban planning to achieve smart and sustainable development goals (SDGs) [7-9]. Figure 1 outlines the key SDGs that guide these urban development aspirations.

Figure 1: Sustainable development goals (www.un.org/sustainabledevelopment).

While the integration of technology in city management is not a novel idea and traces its roots back to the late 1950s and early 1960s, it is only in recent times that the vast potential of these technologies has gained widespread recognition [10, 11]. In the realm of urban planning, the pursuit of SDGs, especially those intricately linked with urban contexts such as SDG 3, 6, 7, 9, 11, and 15 [9, 11], has become more attainable due to rapid advancements in data collection sensors and methodologies [12]. The proliferation of digital data sources, including but not limited to satellite imagery, sensor networks, and social media, has revolutionized our ability to capture and analyze urban phenomena at unprecedented scales [13, 14]. Furthermore, the contemporary landscape is witnessing a surge in the deployment of big data collection sensors, overseeing transformations in land use, transportation patterns, real-estate investments, and energy consumption. This surge is expediting the application of disruptive technologies, both emerging and mature [12]. These disruptive technologies, encompassing artificial intelligence (AI), the internet of everything (IoE), machine learning, deep learning, artificial neural networks, and the advent of 5G/6G, in conjunction with big data, are instrumental in shaping, expanding, and assessing the efficacy of smart and sustainable development initiatives worldwide [15]. Consequently, AI has emerged as a particularly promising technology in the realm of smart and sustainable urban development [12]. Concurrently, advances in machine learning and simulation techniques provide the means to transform raw data into actionable insights [3, 4]. However, existing literature underscores the need for integrated frameworks that harmonize these disparate elements into a cohesive structure capable of simulating realistic urban environments and facilitating informed decision-making [16, 17]. This paper introduces a novel UC framework expressly designed to address the challenges posed by contemporary urban landscapes, with a focus on 3D geosimulation and enlightened prospective analysis. We propose a holistic framework that amalgamates cutting-edge technologies to address this critical gap. By leveraging the synergy between data acquisition, processing, 3D geosimulation, and enlightened prospective analysis, the framework aims to provide a comprehensive toolset for urban planners, policymakers, and researchers. Following this introduction, the subsequent sections of this paper unfold as follows. Section 2 furnishes a succinct elucidation in the form of research background: artificial intelligence in a nutshell. Section 3 intricately delineates the methodological approach, while Section 4 unveils some case studies. The conclusive insights and directions for future endeavors are encapsulated in Section 6.

Research Background: Artificial Intelligence in a Nutshell

In the face of escalating sustainability challenges, cities globally are grappling with unprecedented environmental and socio-economic issues. This urgency has spurred the formulation of sustainable development goals (SDGs) and the inception of smart sustainable city initiatives. These initiatives, leveraging information and communication technologies (ICT), aim to foster sustainable lifestyles and maintain a consistently high quality of life. The integral role of urban computing in advancing smart city development and performance has been acknowledged [1, 3, 6, 8, 12, 16, 21]. Smart sustainable cities, as a fusion of diverse technologies, represent a strategic response to the pressing need for sustainable urban living. This amalgamation, encompassing autonomous vehicles, the Internet of Things (IoT), virtual reality, digital twins, robotics, big data, blockchain, and artificial intelligence (AI), holds transformative potential ([26, 27]. Among these, AI stands out as the most disruptive technology ([26, 27]. In the landscape of urban computing, AI has emerged as a driving force reshaping urban planning and development.

The surge in AI adoption is grounded in its ability to endow machines with human-like intelligence, enabling them to analyze extensive datasets, recognize patterns, and make informed decisions. This aligns seamlessly with the evolving complexities of urban environments, where economic, social, environmental, and governance challenges abound. Researchers emphasize that AI's real impact in cities transcends the technology itself, manifesting in its implementation in urban planning and design [18]. Machine learning, a subset of AI, notably influences the planning process, with urban big data analytics and data-driven planning forming the bedrock of algorithmic urban-planning-based smart and sustainable development [19, 20]. The multifaceted applications of AI in urban computing extend across the globe, with cities in Europe, America, and Asia, including Amsterdam, London, Vienna, Stockholm, Toronto, Singapore, and Hong Kong, harnessing AI to achieve sustainable outcomes in their smart city transformations [21-25].

In urban planning, AI algorithms wield advanced analytics to process intricate spatial data, optimizing land use, facilitating infrastructure planning, and managing traffic [7, 17, 21]. These advancements align harmoniously with the SDGs, particularly those directly relevant to urban contexts ([9]. AI contributes significantly to the realization of SDGs related to health (SDG 3), clean water and sanitation (SDG 6), affordable and clean energy (SDG 7), industry, innovation, and infrastructure (SDG 9), sustainable cities and communities (SDG 11), and life on land (SDG 15).

The versatility of AI is underscored by its role in predictive analytics for optimizing resource allocation and in creating intelligent systems that enhance urban resilience. Ongoing research delves into both current applications and anticipates future possibilities, considering the rapid evolution of both AI technologies and urban computing needs. As we explore the intersection of AI and urban computing in subsequent sections, we delve deeper into methodologies, challenges, and potential trajectories in our holistic framework tailored for 3D geosimulation and enlightened prospective analysis.

Materials and Methods

Working Definition of Urban Computing and Related Concepts

Urban Computing is a multidisciplinary field that represents the convergence of advanced computational methodologies and urban studies. It involves the systematic collection, integration, and analysis of diverse data sources within urban environments, employing cutting-edge technologies such as sensor networks, data analytics, machine learning, and simulation. This field aims to unravel the complexities of urban systems, facilitating informed decision-making for urban planners, policymakers, and researchers. Four related concepts collectively contribute to the comprehensive understanding and application of Urban Computing, offering insights into the trans-formative potential of technology in shaping the future of urban environments.

1. ***Smart Cities*** represent a paradigm shift in urban development, leveraging advanced technologies to enhance the efficiency, sustainability, and overall quality of life within urban areas. Smart Cities utilize information and communication technologies (ICT) to integrate and analyze data from various sources, enabling intelligent decision-making for urban planning, resource management, and citizen services. These cities deploy innovative solutions to address urban challenges, optimize infra-structure, and

improve the well-being of their residents.

2. ***Urban Informatics*** is an emerging field that examines urban phenomena through the lens of ICT, providing insights into the dynamic interactions within urban spaces. Urban Informatics involves the analysis of digital traces and data generated within urban environments, utilizing ICT tools to understand and improve various aspects of urban life, including social interactions, economic activities, and environmental dynamics. It is sometimes confused with UC.
3. ***Geosimulation*** is a computational modeling approach that simulates and analyzes complex spatial and temporal processes, particularly relevant in the context of urban systems. Geosimulation employs computational models to simulate and study real-world phenomena within a spatial context. In Urban Computing, geosimulation is used to replicate dynamic urban processes, such as traffic flow, land-use changes, and population movements, providing a valuable tool for understanding and predicting urban dynamics.
4. ***Prospective Analysis*** involves the systematic exploration and evaluation of potential future scenarios and their implications, providing a forward-looking perspective for decision-making. In the context of Urban Computing, Prospective Analysis employs computational models to assess the consequences of different future scenarios on the urban landscape. It allows decision-makers to evaluate the impact of interventions, policies, and developments, facilitating informed and forward-looking urban planning.

AI-Based Urban Computing Tools and Approaches

The objectives and framework of urban computing give rise to three primary challenges: urban sensing and data acquisition, computing with heterogeneous data, and hybrid systems that seamlessly integrate the physical and virtual realms. Based on Figure 2, Table 1 succinctly categorizes the five techniques frequently employed in urban computing.

Technique	***Description***
Urban Sensing and Data Acquisition	The strides in sensing and data acquisition technologies have yielded an abundance of data in our urban landscapes, encompassing aspects from traffic flow and air quality to social media and geographic data.
Urban Data Management	Data generated in urban spaces typically carries spatial or spatiotemporal attributes. Moreover, an urban computing system often necessitates the adept handling of a diverse array of heterogeneous data.
Knowledge Fusion across Heterogeneous Data Sources	In urban computing scenarios, the need arises to harness insights from diverse data sources, requiring technologies capable of effectively integrating knowledge gleaned from multiple heterogeneous data sources.
Dealing with Data Sparsity	Data-missing issues frequently arise due to various reasons, such as limited user check-ins at specific venues in location-based social networking services or certain venues having negligible foot traffic.
Visualizing Big Urban Data	When discussing data visualization, common perceptions typically revolve around the visualization of raw data and the presentation of results derived from data-mining processes.

Table 1: Five techniques frequently employed in urban computing.

Extracting meaningful knowledge from the voluminous urban data remains a formidable challenge, particularly when modeling the intricate spatial-temporal system, as illustrated in Figure 2 (Decision-making and adaptation). Urban prediction tasks demand the consideration of myriad factors, presenting a complex problem in fully accounting for these interconnected elements. Data-driven intelligent learning has garnered heightened attention in academia, but its performance and efficiency are severely constrained by large-scale real-world variables, posing significant challenges for urban computing.

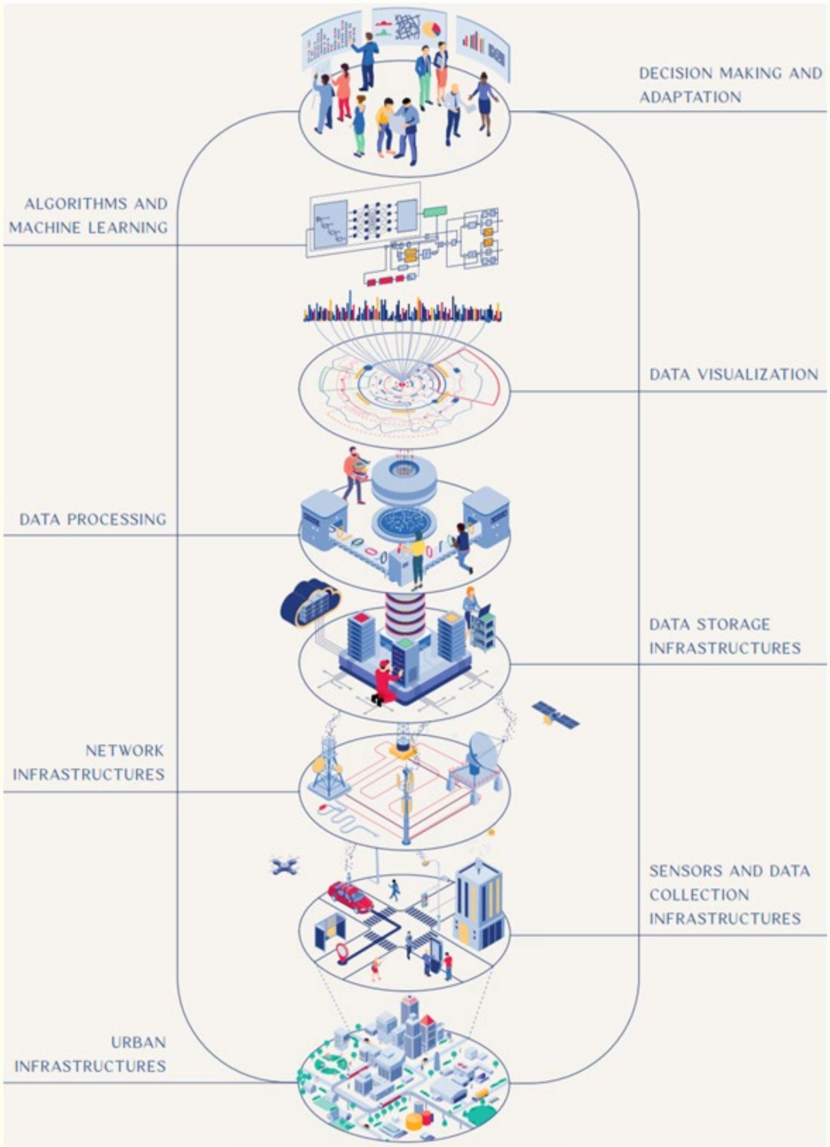

Figure 2: AI-Based Urban Computing Tools and Approaches (Adapted from [18]).

The ultimate aspiration of urban computing is to empower intelligent decision-making at both the macro-level of urban governance and the micro-level of personal life. This encompasses areas such as construction planning, traffic control, logistics optimization, emergency response, epidemic prevention, and control, among others. However, the current applications of urban computing primarily focus on data display or status evaluation, creating a disjunction where the current state of urban computing development does not align with its long-term goals.

Urban Computing Framework for Enlightened Prospective

Despite the challenges inherent in urban computing, recent strides in AI-enhanced spatial-temporal data-mining technology present new opportunities. We are redefining the UC framework in terms of knowledge discovery, system-scale spatial-temporal prediction, causality analysis, and intelligent decision-making, all aimed at advancing urban computing for enlightened prospective applications (Figure 3, Boxes 1, 2, and Box 3). This section focuses particularly on Box 3.

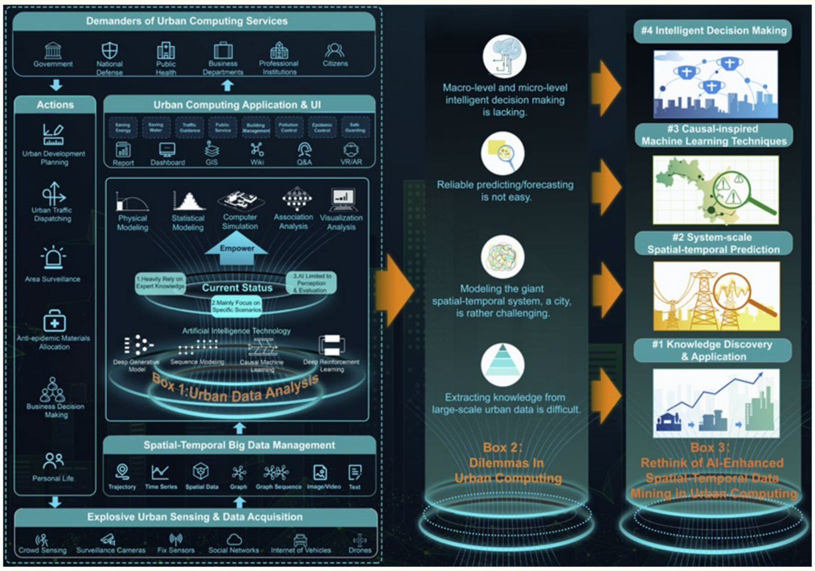

Figure 3: Urban Computing Framework for Enlightened Prospective.

Rethinking Knowledge Discovery and Application: Knowledge discovery and application stand as pivotal stages in urban computing. In recent years, the rapid development of knowledge reasoning has allowed for the representation and discovery of knowledge in real-world scenarios. Transfer learning facilitates information sharing across diverse tasks, aiding models in discovering knowledge with limited data. The decision-making process in reinforcement learning enables the removal of false and noisy data, ensuring the efficacy and quality of knowledge reasoning. Knowledge acquired through collection or inference can furnish abundant external information for various applications, promising enhancements in the effectiveness of existing applications.

Rethinking System-Scale Spatial-Temporal Prediction: A city functions as a vast spatial-temporal system with multiple interrelated variables. In urban computing, a single result often emerges from the interaction of numerous factors. Multivariate time series forecasting allows the construction of a forecasting model for multiple correlated variables, significantly enhancing the forecasting effectiveness for each variable. This approach finds application in real-world scenarios such as weather and traffic forecasting. The development of Transformer and its variants in recent years enables long-term predictions, broadening our perception of the future. Furthermore, graph neural networks, gaining prominence, effectively utilize the graph structure to model dependencies between various variables. Integrating graph neural networks to model spatial relationships may bolster the performance of urban computing applications. Building large-scale, pre-trained models based on historical data is also a future direction in urban computing to further enhance data utilization.

Rethinking Causal-Inspired Machine-Learning Techniques: Causality serves as a crucial tool for understanding how the physical world operates. Integrating causality into DNN models has emerged as a promising research direction to enhance the reliability of

AI algorithms. Recent causal AI techniques have proven valuable in improving the reliability of prediction, classification, and decision-making. In urban computing, many applications can be conceptualized as causal problems. For instance, scheduling traffic lights requires an understanding of the causality of traffic jams. Infusing causal mechanisms into AI models holds the potential to benefit various urban computing tasks, though such endeavors are currently scarce.

Rethinking Intelligent Decision Making: Urban decision-making involves navigating complex systems. Traditional algorithms grapple with the challenge of high model complexity and heavy computations. The need arises to model large amounts of high-dimensional variables with various distributions, which proves intractable without simplifications. Simultaneously, the decision action space is exceedingly large, surpassing the capabilities of traditional methods to provide feasible solutions within an acceptable timeframe. Contrastingly, recently developed data-driven decision-making models demonstrate advantages in solving complex problems. These models naturally suit the handling of high-dimensional variables and facilitate parallel processing.

Case Studies

Studies Settings

To empirically validate the efficacy of the proposed Urban Computing frame-work, two distinct case studies in diverse urban contexts were analyzed: 1) Complex parking regulations and curb use restrictions in Los Angeles; 2) Air quality monitoring in Vilnius, Lithuania.

The City of Los Angeles is incorporating AI into its operations to enhance service delivery, foster connectivity, and address inequalities across its vast and diverse population. Aligned with the SmartLA 2028 strategic plan, released in 2020 [28], city departments, including the Los Angeles Department of Transportation (LADOT), are actively working towards technology goals such as improving infrastructure, enhancing data tools and practices, advancing digital services, promoting connectivity and digital inclusion, and refining governance. LADOT, specifically focused on infrastructure and mobility, initiated a curb digitization and asset management project.

The City of Vilnius in Lithuania is actively integrating data-driven decision-making into its planning and operations, with a focus on utilizing key performance indicators (KPIs) as the primary evaluation method for proposed projects and programs. In collaboration with Breeze Technologies [29], a platform-based air quality monitoring company, the planning authority, has implemented air quality sensors throughout the city. The collected data from these sensors supports planning initiatives related to transportation, urban ecosystem planning, and promoting healthier living. Artificial intelligence plays a dual role in this project, handling both data processing and predictive analytics.

These case studies showcase the framework's versatility in addressing real-world urban challenges and providing actionable insights for decision-makers.

Complex parking regulations and curb use restrictions in Los Angeles

Problem Identification and Planning: Los Angeles faces challenges related to complex parking regulations and curb use restrictions, prompting a need for dynamic curb management. The City Council and LADOT prioritize this as a strategic goal. However, the absence of a comprehensive repository for current curb uses and regulations impedes effective planning for network circulation improvements. Initially planning a five-year roadmap for digitizing all curb assets, budget constraints led to a scaled-down pilot program in three dense commercial areas. The pilot aims to address key questions about asset collection methodologies, the impact of land use context on data collection, and the optimal and scalable solution for curb digitization.

Data Collection: Los Angeles focused on obtaining relevant information on curb use restrictions, parking regulations, and other assets in the public right-of-way. This encompassed details such as curb length, location, color, parking location, timing, and parameters. Although information existed in the streetscape, there was no consolidated and machine-readable dataset. Manual data collection by walking every foot of curb space was deemed impractical, leading LADOT to partner with IBI Group and their CurbIQ platform [30]. This platform utilized artificial intelligence-enabled curb data collection methods, primarily mobile mapping, with the aid of car-mounted smartphone cameras. IBI Group's data collection involved imaging and classifying the curb, supplemented by citation data for quality assurance and quality control. Two primary technologies were employed: the SharedStreets CurbWheel, a manually-operated device for precise measurements but requiring more time, and car-mounted smartphone cameras for faster data collection through AI data pro-cessing. While the CurbWheel offered high accuracy, the smartphone camera and AI process, while faster, exhibited lower accuracy in densely populated areas.

Data Processing and AI Integration: In terms of artificial intelligence, the primary technologies employed in the project were diverse machine-learning models. Computer vision models were utilized for object identification within cameras and videos, while text comprehension models were deployed to interpret signage. Additionally, Geographic Information Systems (GIS) played a crucial role in associating footage and generated data with specific data collection locations, facilitating the mapping of curb uses and restrictions. Notably, as the vendor handled all processing aspects, LADOT was relieved from the responsibility of constructing or maintaining any technological infrastructure for these processes.

Data Analysis/Visualization and Decision Making: For data visualization in this project, LADOT exclusively utilized the CurbIQ platform, a custom-built solution by IBI Group. The data collected in the pilot, along with future data from the broader Code the Curb program, will be the foundation for three main analysis projects planned by LADOT. These projects aim to enhance curbside asset management, identify optimal locations for zero-emissions delivery zones, and improve enforcement of curbside restrictions. To enable the enforcement aspect, the city needed to pass an ordinance. While the pilot's scope didn't cover the entire city, it proved valuable in supporting analyses in targeted neighborhoods. Furthermore, it garnered confidence among city council members and showcased tangible progress aligned with the strategic goals set by the council and the department.

Principal insights: The case study underscores the effectiveness of UC projects, even without extensive data collection systems. The temporal nature of the Code the Curb project, where curb uses and signage change over months or years, allowed for less frequent data sampling. LADOT tailored the solution to focus on key locations and discrete data collection efforts, reducing costs and project timelines while still achieving meaningful results. This approach makes the techniques used in the Los Angeles pilot applicable to smaller municipalities lacking the resources for citywide urban sensors, enabling them to engage with AI and design more tailored implementations.

Air quality monitoring in Vilnius, Lithuania

Problem Identification and Planning: Vilnius focuses on three KPIs (a happiness index, a travel time index, and life expectancy) to enhance city services. Resident surveys highlighted air quality and pollution as major concerns impacting these KPIs. In response, Vilnius initiated a sensor system to promptly address air quality issues, aligning with its goal of building a comprehensive information ecosystem. This initiative aims to support better planning for improved air quality and make air quality data accessible to citizens, contributing to the city's vision of connecting people across industries and sectors.

Data Collection: In Vilnius, despite a few outdated air quality sensors, monitoring and responding to air quality relied heavily on citizens reporting issues in the recent past. This led to a temporal gap between citizen reports and city technicians' response. To address this, Vilnius collaborated with Breeze Technologies [29] to implement a real-time sensor system. These sensors collect data on temperature, humidity, climate, and pollutants, offering a comprehensive view of the local environment. This initiative aims to minimize the delay in assessing and responding to air quality issues by providing accurate and timely data.

Data Processing and AI Integration: To enable near real-time air quality monitoring, Breeze Technologies employs cloud-based AI methods to process and calibrate data collected by sensors. AI is primarily utilized for outlier detection, ensuring accurate interpretation of data by identifying anomalous points. Additionally, AI monitors sensor health, enabling proactive replacements before failure, and incorporates inherent sensor characteristics to better interpret raw data in different conditions.

Data Analysis/Visualization and Decision Making: The Breeze platform, integrated with AI technologies, utilizes algorithms to interpolate between sensors, filling data gaps and expanding coverage across Vilnius. AI is also employed for modeling clean-air interventions and predicting outcomes based on the context of previous interventions. Future plans include integrating Breeze data with Vilniaus Planas' Mobility-as-a-Service (MaaS) platform for AI-enabled transport network and traffic engineering modifications. Key skills employed by Breeze Technologies include im-plementing AI algorithms and data integration technologies. The city's overarching goal is to enhance collaboration between departments and citizens, fostering an "Intelligent City Brain" to prioritize efforts for the greatest impact on citizens' quality of life. Well-defined performance metrics, citizen dialogues, and data-facilitated inter-departmental collaboration are emphasized. AI plays a crucial role in uncovering insights, and strong data sharing and transparency frameworks are considered essential for this work, as evident in Vilnius' and Breeze's commitment to publicly available data.

Principal insights: The Air Quality Monitoring use case in Vilnius represents a fully out-of-the-box UC project implementation. In this approach, an external service provider manages most aspects of the process, including sensor installation, data storage, processing, visualization, and AI integration. This out-of-the-box strategy enables municipalities of various sizes and technical capabilities to engage in UC, with the service provider handling the majority of tasks. However, the Vilnius case study emphasizes that adopting an out-of-the-box solution doesn't mean sacrificing agency and oversight. Municipalities can still actively manage and supervise projects, taking a collaborative approach to tailor the solution to their specific contexts and citizens' needs. Understanding each step of the process is crucial, and as highlighted by the Vilnius case study, municipalities can integrate data and model results into existing visualization and decision-making platforms. This ensures that insights align with the goals and activities of other city departments and sectors, allowing for a more cohesive and effective use of artificial intelligence in urban settings.

Conclusion and Future Work

Urban planning and design represent intricate fields of study that integrate a diverse range of disciplines. Collaborative efforts among city planners, urban designers, architects, and landscape architects are essential in addressing challenging urban issues. This paper has immersed itself in a comprehensive approach to address the intricate challenges faced by urban planners, policymakers, and researchers. The amalgamation of cutting-edge technologies in data acquisition, processing, 3D geosimulation, and prospective analysis marks a significant stride towards a more informed and dynamic urban planning paradigm. The integration of AI-based tools and approaches has showcased promising results in enhancing the accuracy and efficiency of urban simulations, thereby empowering decision-makers with valuable insights for sustainable urban development. The deployment of sensors and advanced data collection techniques has contributed to a richer understanding of urban dynamics, offering a solid foundation for evidence-based policymaking. The two case studies demonstrate partially the practical application of the components detailed in Figures.

Looking ahead, the future work in this domain holds tremendous potential for further refinement and expansion of the proposed framework. Continued collaboration between academia, industry, and municipal bodies is crucial to advancing the field of Urban Computing. In particular, future research endeavors could focus on refining AI algorithms for enhanced geosimulation, incorporating more diverse and real-time data sources, and exploring the scalability of the framework for application in different urban contexts. Furthermore, the framework's application in real-world case studies has laid a foundation for assessing its practicality and effectiveness. Ongoing and future case studies will provide valuable feedback and insights, enabling iterative improvements and ensuring the adaptability of the framework to evolving urban landscapes.

The presented holistic framework not only contributes to the academic discourse on UC but also holds significant promise for practical implementation in urban planning and governance. As we navigate the complex challenges of urbanization, this framework stands as a beacon towards a more sustainable, data-driven, and enlightened urban future.

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